Improving Short-Range Cloud Forecasts in Harmonie-Arome Through Cloud Initialization Using Mesan Cloud Data

Förbättring av korta molnprognoser i HARMONIE-AROME genom moln-initialisering med MESAN-molndata
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Abstract

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Previous studies, such as van der Veen (2012) and White et al. (2017), have demonstrated the potential of using measurement-based cloud data to improve Numerical Weather Prediction (NWP) based cloud forecasts. This can be done through cloud initialization; a process of injecting cloud data after the regular data assimilation in an NWP model. The purpose of this study was to use cloud data from the Mesoscale Analysis system MESAN to investigate cloud initialization in the HARMONIE-AROME model system for improving short-range cloud forecasts. The cloud initialization method that was used was similar to a method used by van der Veen (2012), where specific humidities, temperatures, and hydrometeor concentrations were altered using information on cloud fractions, cloud base heights and cloud top heights. MESAN input data analyses as well as cloud initialization investigations were carried out.

MESAN input data analyses revealed significant differences in cloud fractions between MESAN and the background model field in MESAN. Overestimations of cloud fractions in MESAN over sea were caused by satellite data, particularly due to the inclusion of the fractional cloud category. Underestimations of cloud fractions over land were caused by limitations of the synoptic weather (SYNOP) stations in measuring clouds. Furthermore, larger differences between MESAN and SYNOP were found over Sweden and Finland compared to Norway, which may be tied to Norway having mostly manual SYNOP stations, and Sweden and Finland having mostly automatic stations.

Shortcomings were found in the investigated cloud initialization method. Such shortcomings involved a limit check on the specific humidity change, the cloud initialization being repeated for an unnecessarily large amount of iterations, and the use of a sub-optimal profile of critical relative humidity. Using a one-dimensional vertical column version of HARMONIE-AROME, named MUSC, to integrate forward in time revealed a large sensitivity to the use of forcing profiles and forcing time scales in MUSC. Alterations made through cloud initialization were found to last over 12 h, with varying effects depending on the investigated height. A reasonably good agreement between MUSC results and results from the three-dimensional version of HARMONIE-AROME was found. Findings in this thesis point at potential to further enhance the HARMONIE-AROME cloud initialization technique. These enhancements concern a revised MESAN cloud product and taking care of some flaws in the cloud initialization method.

Keywords: cloud initialization, HARMONIE-AROME, MESAN, satellite product, synoptic weather station

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Populärvetenskaplig sammanfattning

Förbättring avorta molnprognoser i HARMONIE-AROME genom molninitialisering med MESAN-molndata

Joakim Pyykkö


Analyser av indata till MESAN visade på över- och underskattningar av moln i satellitdata över hav och underskattningar av moln i SYNOP-data över land. För satellitdatat berodde detta på medtagande av moln på liten skala eller väldigt tunna moln, medan det för SYNOP berodde på begränsningar i mätmetoderna. Det fanns även en skillnad i kvalitet i SYNOP-data i Sverige och Finland gentemot Norge, vilket kan bero på att de flesta mätstationer i Norge är manuella medan de flesta i Sverige och Finland är automatisera.

Molninitialiseringsmetoden bestod i att extrahera data om molnbashöjd och molntopphöjd från MESAN, och sedan modifiera fuktighet, temperatur och hydrometeorer (såsom molndroppar och i skristaller) i HARMONIE-AROME utifrån molnens position. Brister i metoden hittades. Initialiseringsprocessen upprepades ett suboptimalt antal gånger. En begränsning i hur mycket fuktigheten tillåts modifieras förändras under initialiseringsprocessen och fungerade inte som avsett. Dessutom, jämförelse med radiosondadatal pekar på att relativa fuktighetsgränserna för villket moln bildas inledningsvis inte ansattes korrekt. Effekterna av metoden kunde vara i över 12 timmar, men denna studie pekar på ytterligare troliga förbättringsmöjligheter i HARMONIE-AROME genom införande av reviderad version av metoden samt förbättrade satellitprodukter.

Nyckelord: molninitialisering, HARMONIE-AROME, MESAN, satellitprodukt, synoptisk väderstation

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1 Introduction

Numerical Weather Prediction (NWP) models for weather forecasting purposes are used for different time scales; from a few hours, called a nowcast, up to several weeks. The skill and accuracy of such a model is of great interest to meteorologists and researchers, as they want to provide useful forecasts to businesses affected by weather, and the general public. In order to provide an accurate forecast, an NWP model has to take a lot of variables into account, for example, temperature, precipitation, cloudiness, and humidity. These provide various challenges for the researchers struggling to improve such models.

When improving NWP model forecasts, one methodology is to use new data types to improve the initial state of the model, and then monitor how well the change improved the forecast, for how long the change had an effect, and how different variables were affected. The usability of such a change differs between different time-scales. A short-time effect might not be useful for a forecast of a couple of weeks but may be useful for short-range forecasts. Forecasts that range up to approximately nine hours are usually referred to as nowcasts.

One particularly difficult aspect to consider in an NWP model is the cloudiness. Clouds can be found at many different heights in the atmosphere, mostly in the troposphere; there are different types depending on the occurring weather situation, and there can even be multiple layers of clouds above one particular location of the surface. There are many aspects of clouds that make them important to forecast, such as the formation of precipitation and thunder, the changes in the radiation balance at the Earth’s surface, and the effect on aviation.

Several ground-based methods of measuring clouds exist today; the classical method is for an observer to make note of the cloud types and the amount of sky covered by clouds, and another is automatic measurements, such as from a ceilometer, which measures the distance from the ground to the cloud base. The observer method presents some uncertainties due to the subjectivity of such a method (SMHI, 2017). Automatic stations come with their own caveats, such as biases and calibration issues, but they are more reliable at measuring several layers of clouds than an observer. They also provide a more objective way of quantifying measurement errors. Another common way of observing clouds is through satellite imagery. These products are based on measurements from instruments placed on-board geostationary and polar-orbiting satellites. Geostationary satellites stay in orbit just above the equator, which can cause issues when scanning locations far north, such as northern Europe, due to the steep viewing angle. Polar-orbiting satellites might be more suitable for cloud imaging in northern Europe partly thanks to their lower height above the surface of the Earth than geostationary satellites, but also thanks to their paths from pole to pole as they scan the Earth. However, the temporal resolution is significantly lower. Satellite based measurements might have problems detecting layers of clouds and to separate clouds from the underlying surface.
Issues when comparing models and measurements may rise simply from the different treatments of clouds in both the NWP models and the measurements. For measurements, an observer may divide the sky into eight parts (oktas), and look at the total amount of clouds in each okta; meanwhile, a ceilometer may only look straight above it, not giving any immediate information on the total cloud cover surrounding the instrument (Met Office, 2018). Satellite products are limited by their spatial and temporal resolutions, which vary between instrument and satellite types. NWP models may handle microscopic and macroscopic parameters separately. For macroscopic variables, a model may calculate the cloud fraction using the relative humidity. This is the amount of one grid point, from 0 to 1, that is covered by clouds (Arbizu-Barrena et al., 2015). Translating between the different ways of treating clouds may cause difficulties during evaluation of model and measurement cloud data.

Forecasting in general involves continuous cycles of NWP model runs, where measurement data are added to update the model state through a process called data assimilation in order for the physical fields in the model to represent the current state of the atmosphere. Among those measurement data are typically observations of variables such as temperature and air pressure. Cloudiness may not be directly inserted as measurements in some models, which means that the clouds would then be assumed to adjust through the other physical fields. However, van der Veen (2012) found that when initializing the High Resolution Limited Area Model (HIRLAM) using cloud mask imagery from the Second Generation Meteosat satellite, there is still a positive impact on the quality of the forecasts after 24 hours in 59% of the cases studied. Bayler et al. (1999) found that cloud initialization using sounding data from the Geostationary Operational Environmental Satellite (GOES) improved the coverage of non-precipitating clouds in the first 24 hours of forecasts from four model setups. All of this suggests that cloud initialization might have significant positive effects on forecast, especially for nowcasting.

The purpose of this thesis is to study the possibility of using cloud initialization for improving NWP based cloud nowcasts. This thesis uses model and measurement data procured by the Swedish Meteorological and Hydrological Institute (SMHI), from the HARMONIE-AROME operational forecast system and the Mesoscale Analysis system (MESAN). The data covers northern Europe and are for the months April, May and June during the year 2017. Firstly, the cloud data from MESAN are compared with three of the sources that are used in the analysis model: ground-based synoptic measurements, satellite data, and the background model field used in MESAN. This is to quality-check and validate the data that will be used for cloud initialization. No reliable independent cloud observations not used by MESAN were available. Otherwise, such independent data would have been an appropriate source to validate against. Secondly, with a one-dimensional model framework, the effects of initializing the model with cloud observational data from MESAN are compared to model runs with no such cloud initialization in order to analyze the effects on nowcasting. Finally, results from a one-dimensional
framework are evaluated alongside results from the three-dimensional version of HARMONIE-AROME. For all of these investigations, both statistical and subjective methods are used.

## 2 Background

### 2.1 System overview

This work is concerned with evaluating and investigating a system that is composed of a traditional NWP component combined with a cloud analysis component. The design of this combined system is given in Figure 1. The NWP initial state is usually obtained by merging a model background state with various types of observations. Here we also utilize MESAN clouds when deriving the initial state of the model, applying an innovative cloud initialization technique. The MESAN clouds are based on a combination of sources such as satellite products, synoptic weather stations (SYNOP) and a model run, or a background model field as it will be referred to as. From the produced initial state, the forecast model is then integrated forward in time to produce a forecast.

![Diagram](image)

**Figure 1.** The combined NWP and cloud analysis system. Main system components are represented by boxes and data by circles.
2.2 NWP

2.2.1 Introduction to NWP

NWP is the process of predicting future weather using numerical methods. An NWP model combines known theories of atmospheric research with observational data and integrates forward in time. This gives a prediction of the future state of the atmosphere. In Figure 1, the NWP part is represented by the lower two boxes.

In an NWP model, either the entire Earth, or a limited area of the Earth is modeled. An example of a global NWP model is the Global Forecast System (GFS), which is a global model system consisting of four coupled models for the atmosphere, the oceans, the soils, and the sea ice (NOAA, 2016). These models are suitable for planetary- and synoptic-scale weather systems, as they have coarse resolutions. Limited-area Models (LAM) are used to simulate weather on a finer scale, in a defined limited area of the Earth. An example of LAM is the HARMONIE-AROME operational forecast model.

Both global models and LAM require initial data when making a forecast to accurately represent the present state of the atmosphere before the forecast model is integrated forward in time. For a LAM, the model initial state can be derived through data assimilation of observations, or it can be taken from a global model state, interpolated to the limited area geometry. The latter is sometimes referred to as downscaling. Data assimilation in NWP is concerned with utilizing various types of observations to obtain the best possible initial state. Since the number of observations is small in some areas, a so-called background state is needed to get starting values in all grid-points. Usually, a short-range forecast from a previous model run valid at the time of the observations is used. Also important for LAM is the input of boundary conditions. LAM typically take their boundary conditions from global models, such as the GFS. At the boundaries of the LAM, a buffer zone exists, which serves as a zone where the fields from the global model are allowed to adapt to the LAM. Forecasts may be affected by this near the lateral boundaries (Warner, 2011). In HARMONIE-AROME (cycle 40h1.1), the lateral boundary conditions are taken from the ECMWF model (Bengtsson et al., 2017).

2.2.2 Governing equations

NWP models make use of a combination of fluid-dynamic and thermodynamic equations. They can take into account many important processes of atmospheric motion and thermodynamics. The basic set of equations that serve as a basis when creating an atmospheric model are as follows:

\[
\frac{\partial u}{\partial t} = -u \frac{\partial u}{\partial x} - v \frac{\partial u}{\partial y} - w \frac{\partial u}{\partial z} + \frac{uw \tan \phi}{R} - \frac{uw}{R} - \frac{1}{\rho} \frac{\partial p}{\partial x} - 2\Omega (w \cos \phi - v \sin \phi) + F_x \tag{1}
\]
Here, Equation 1-3 are the Navier-Stokes Equations for the motion in the longitudinal \((x)\), latitudinal \((y)\), and the vertical \((z)\) direction respectively, with terms that account for the curvature of the Earth added. Equation 4 is the Thermodynamic Energy Equation, 5 is the Continuity Equation for mass, 6 is the Continuity Equation for water vapor, and 7 is the Ideal Gas Law. The \(u\), \(v\), and \(w\) are the wind speeds in the \(x\)-, \(y\)-, and \(z\)-directions, \(\phi\) is the latitude, \(R\) is the radius of the earth, \(\Omega\) is the rotational frequency of the earth, \(p\) is the air pressure, \(\rho\) is the air density, \(F\) is the friction term in each direction, \(T\) is the temperature, \(\gamma\) and \(\gamma_d\) are the temperature lapse rate and the dry adiabatic lapse rate respectively, \(c_p\) is the specific heat capacity at constant pressure of the air, \(H\) is the heat gain or loss, \(q\) is the specific humidity, \(Q\) is the loss or gain of humidity from phase changes, and \(R\) is the universal gas constant (Warner, 2011). When constructing a model, these equations may not necessarily be used in the forms present in Equation 1 through 7. Many simplifications can be made, such as for a hydrostatic model, which simplifies Equation 5 to a simple balance between the pressure gradient force and the gravitational force (term 5 and 7 on the right-hand side). This assumption saves on computing resources, however, such a model can not model vertical accelerations. In the case of HARMONIE-AROME, a non-hydrostatic dynamical core is used (Bengtsson et al., 2017).

### 2.2.3 Grid-point and spectral method

When integrating the governing equations forward in time, some type of spatial and numerical discretization in space and time is required. Two widely-used ways of spatially representing the physical fields in an NWP model are the grid-point method and the spectral method. Grid-point methods divide model data into discrete grid-points and solves the governing equations
for each grid-point. This means that the resolution is directly governed by the distance between the grid-points. Spectral methods, however, represent the data as a series of continuous wave functions. The resolution then comes from the limitations in the size of the smallest wavelength that can be modeled (Warner, 2011). HARMONIE-AROME uses the spectral method.

2.2.4 Physical parameterizations

Parameterization is the process of expressing unknown variables in terms of known variables. Many of the atmospheric processes occur on such a small time- and spatial scale that it is not realistic for NWP models to model these directly. These models instead use parameterization schemes. Processes that are typically parameterized are turbulence, surface and atmosphere heat fluxes, soil and vegetation, convection, radiation and cloud microphysics. Thus, a typical example would be turbulence, where the smallest turbulent eddies can reach sizes of a few millimeters. For example, a simple turbulence parameterization scheme involves expressing the atmospheric heat fluxes as a function of the mean vertical wind gradient (Stensrud, 2007).

2.2.5 Modelling of clouds

As the spatial scale of clouds can vary drastically depending on the type of cloud, certain clouds may need to be parameterized and others explicitly modeled. Specifically, cumuliform clouds exist on a rather small horizontal scale, which creates the need for a high enough resolution in the model lest they need parameterization. For clouds, the microphysical processes occur on a very small spatial scale, meaning that these processes always require parameterizations in a forecast model. The macroscopic properties of cumuliform clouds can be explicitly resolved with a high enough resolution. Many stratiform clouds, on the other hand, already exist on a large enough horizontal scale that there is no need for parameterizations of their macroscopic properties. It should be noted that such macroscopic features such as cloud cover can still require parameterization schemes given large amounts of sub-grid clouds (Stensrud, 2007).

Microphysical processes in a cloud involve the distribution of hydrometeors, and the processes by which these changes. These happen far under the grid-scale of conventional forecast models. Two types of microphysics schemes are typically used, and the difference is how they handle the hydrometeor distributions. Bulk parameterization schemes use a continuous function for the particle size distributions of all types of hydrometeors involved. Bin schemes divide the sizes into bins, and calculate the concentrations for each bin. Also, there are schemes called single-moment schemes and double-moment schemes. Single-moment schemes only calculate the particle mixing ratio, while double-moment schemes are also capable of calculating number concentrations (Stensrud, 2007).

HARMONIE-AROME uses a single-moment bulk parameterization scheme named ICE3
(Pinty & Jabouille, 1998). The hydrometeors are: cloud ice, snow, graupel and hail. The cloud cover in this model is not determined prognostically, and is instead modelled using a cloud and condensation scheme. The horizontal resolution is 2.5 km, and 65 vertical levels with a top at 10 hPa are used, which means that deep convection is resolved directly in the model, while shallow convection requires a parameterization scheme (Bengtsson et al., 2017). Corresponding atmospheric pressures and heights for each model level, assuming standard sea-level pressure, can be found in Table in the Appendix.

2.3 Cloud observations

Observations of clouds can be done through many different measures. These include both instrumentation and human observers. This section, and the following about MESAN, are represented by the upper box in Figure. Following is a list of some measures used for cloud observations, with information about the methodology, the usefulness, and the errors and uncertainties:

- **Human observations** – For the longest time, human observers were the most widely-used method for observing clouds. This is done by a person seeing the sky as being divided into eight parts, or oktas, and then determining how many oktas are covered by clouds. The cloud cover over the area of the measurement station is then determined. The cloud amount goes from 0 (no clouds), up to 8 (complete cloud cover), with an exception of 9, which means that the sky is unobservable due to fog or other phenomena that obscure the view (Met Office, 2018). One of the largest sources of uncertainties in these types of measurements is the subjectivity. Observations of the same situation can be different depending on the person doing them. The accuracy of cloud observations by human observers is estimated by Boers et al. (2010), by comparing a one-year instrumental experiment with a thirty-year climatological record of human observations, to be around one okta.

- **Ceilometers** - A ceilometer is an instrument that detects whether a cloud is present in the direction that it points, measuring the distance to the cloud. It is a typical instrument for cloud measurements at an automatic weather station, and it has replaced human-based observations in many places. A laser-based ceilometer is a type of Lidar (Light Detection and Ranging), which works by pointing a beam of light at a location and measuring the backscatter (NOAA, 2012). Ceilometers can be used to determine the cloud cover over an area. This is determined by the amount of time that the ceilometer does or does not detect a cloud in the direction that it is facing. An objective way of determining cloudiness from measurements and also a good temporal resolution is obtainable from this method. However, one major flaw is that the sky cover is then approximated as what is in direct line of sight of the ceilometer. Clouds may still be present but can be missed by the ceilometer (Wagner & Kleiss, 2016). As shown...
by Wagner and Kleiss (2016), ceilometers used by the Atmospheric Radiation Measurement (ARM) Southern Great Plains (SGP) Central facility also have a height limit of almost 3700 m for detecting cloud bases, which is also a significant flaw when observing clouds. This height limit is around 7600 m for synoptic weather stations in northern Europe, however.

- Satellite measurements – For cloud imaging through satellite imagery, passive radiometers are used, which means that the radiation from the clouds are measured by the satellite sensors without the satellite sending out any signals itself. This radiation is measured in discrete radiation bands, or channels, in the radiometer. One example of such an instrument is the Advanced Very High Resolution Radiometer (AVHRR), for which the latest version is carried by the NOAA-15 satellite. AVHRR measures in six discrete bands that can be used for daytime- and nighttime cloud observations, as well as surface measurements (NOAA, 2017). These measurements do not suffer from the same flaws as ceilometers when measuring macroscopic properties of clouds.

Satellite imaging allows for larger spatial scale measurements of clouds than automated ground-based stations (Garatuza-Payan, Pinker & Shuttleworth, 2000). One problem with using satellite imaging for cloud observations is that the quality of cloud observations is limited by the resolution of the satellite image, and the viewing angle. Geostationary satellites stay above the equator, which causes the viewing angle when viewing higher latitudes to be quite steep. They provide good temporal resolution, however. For the viewing angle problem, polar- or near-polar orbiting satellites may be useful. These make rotations from pole to pole around the earth, giving good resolution images. Polar-orbiting satellites also have lower orbits than geostationary satellites. They do still suffer from having lower resolution with steeper viewing angles, but their paths allow them to occasionally measure straight down at higher latitudes. Due to their large path, however, they do not provide as good temporal resolution as geostationary satellites over one specific area (Stern & Peredo, 2001). There are also other general issues with satellite imagery. When the surface is covered by ice or snow, it might be difficult to distinguish between the surface and high clouds. Also, multiple layers of cloud are hard to detect, and cloud bases are hard to determine.

2.4 MESAN

As the demand for useful observational datasets increases with time, the need for gridded analysis datasets combining different observations has arisen. MESAN, developed by SMHI, is just such a system. The main idea behind MESAN is that observations of different kinds are combined with an NWP model run to create a two-dimensional gridded system, where data are interpolated such to have a quite fine resolution, also covering locations that normally are without observations of any kind. The analyzed grid-point data is calculated as the sum of
the grid-point model point as a first guess, and the difference between the observations and
the model data, with a weighting constant depending on the type of observation. After the
grid-point data has been calculated, it is then quality controlled to ensure that there are no
significantly large deviations (Häggmark, Ivarsson & Olofsson, 1997).

MESAN takes many different sources into account for the calculation of the many mete-
orological variables. The first-guess model currently used is a short-range forecast from the
operational HARMONIE-AROME model, developed through a cooperative effort of many Eu-
ropean countries. It is a high-resolution limited-area model, allowing it to be used for the
high-resolution gridded data system MESAN (SMHI, 2014). The background model data is
then combined with observational data from radars, (mostly) automatic observation stations,
satellites etc. This broad spectrum of different observational data allows for high-resolution
gridded data of precipitation, temperature, wind, clouds, and more (Häggmark, Ivarsson &
Olofsson, 1997).

Cloud observations in MESAN are handled through a combination of satellite data and
synoptic weather stations, with the addition of a background cloud field from HARMONIE-
AROME. From MESAN, the cloud base and cloud top height, as well as the cloud fraction, are
derived. Over sea, satellite based measurements are the only complementary information to the
background model field. Synoptic observations are mostly non-existent over water. Over land,
they do, however, remain a useful way of giving complementary information to satellites and
model data.

2.5 Cloud initialization

The HARMONIE-AROME operational forecast system does not directly incorporate cloudi-
ness in its regular data assimilation cycles. Instead of directly injecting cloud information, the
cloudiness is allowed to adjust through the other physical fields in the model system. This
can cause discrepancies between modelled and observed clouds during the initial hours of the
model run, limiting the usefulness of such a forecast for nowcasting purposes. One way in
which this might be alleviated is through the insertion of clouds from the MESAN system, and
that is the purpose of this thesis. The insertion of clouds from MESAN was done by modifying
the physical variables for each horizontal model grid point, and for each vertical layer, using
information on cloud tops, cloud bases and cloud fractions from MESAN. For converting cloud
fractions at different heights within a vertical column into a single value as seen from below
the column, HARMONIE-AROME uses a method called Maximum Random Overlap (MRO).
The total cloud cover $CC_{ij}$, as seen below the column at horizontal position $i, j$ (grid-point
indices in the x- and y-direction), with $C_k$ being the cloud fraction at vertical model level $k$,
and $n$ being the number of model levels, is given by the following (Morcrette & Jakob, 1999):
\[ CC_{ij} = 1 - \prod_{k=1,n} \frac{1 - \max(C_k, C_{k-1})}{1 - C_{k-1}} \quad (8) \]

Thus, MRO is used to estimate the two-dimensional model cloud cover from the three-dimensional field.

Specific humidity, temperature and hydrometeor concentrations are altered through the initialization. The initialization process is similar to van der Veen (2012), where cloud data derived from satellite imaging was used to initialize clouds in the HIRLAM model.

Where a cloud exists according to the MESAN data, the specific humidity of the model is set to the saturation specific humidity, which is calculated using the temperature and the pressure. Also, the temperature is used to determine whether the saturation specific humidity with respect to liquid water or with respect to ice is used. Two threshold temperatures are used: over 253.16 K for liquid water and under 223.16 K for ice. These values are based on typical temperatures when water and ice clouds, respectively, exist. Between these temperatures, a weighted average between the two saturation specific humidities is used.

Inside the cloud, the specific humidity is set to be equal to the saturation specific humidity, as described by Equation 9. Below and above the cloud, the specific humidity is set to a fraction (CCC) of the saturation specific humidity, which is illustrated in Equation 10.

\[ q_m = q_s \quad (9) \]
\[ q_m = CCC \cdot q_s \quad (10) \]

Here, \( q_m \) is the model specific humidity, \( q_s \) is the saturation specific humidity, and \( CCC \) is a variable related to the critical relative humidity. The \( CCC \) used is calculated as follows:

\[ CCC = RH_{max} - (RH_{max} - RH_{min}) \sin \left( \frac{\pi p}{p_s} \right) \quad (11) \]

Here, \( p \) is the pressure, \( p_s \) is the surface pressure, and \( RH_{max} \) and \( RH_{min} \) are the maximum and minimum critical relative humidities. These maximum and minimum critical relative humidities pertain to the relative humidities of which clouds start to form, where this critical relative humidity is assumed to be highest near the surface and near the tropopause, and lowest in the middle of the troposphere (van der Veen, 2012). Molod (2012) used Atmospheric Infrared Sounder (AIRS) data to investigate critical relative humidities (through the use of a proxy for critical relative humidity), and found a minimum in the mid-troposphere in many cases when investigating monthly averages over different locations and surfaces. Maximum critical relative humidities were found near the surface and near the tropopause level as well (Molod, 2012). Thus, the use of this type of profile has some experimental basis. There are, however, major
uncertainties concerning the assumed $CCC$ profile, and it is dependent on horizontal resolution and model parameterizations. This uncertainty is illustrated in Quaas (2012).

For $RH_{\text{max}} = 0.65$ and $RH_{\text{min}} = 0.58$, $CCC$ is illustrated in Figure 2:

![Figure 2. Vertical profile of CCC with $RH_{\text{max}} = 0.65$ and $RH_{\text{min}} = 0.58$.](image)

Also, other formulations for $CCC$ were investigated:

$$CCC = RH_{\text{min}} + (RH_{\text{max}} - RH_{\text{min}}) \sin \left( \frac{\pi p}{p_s} \right)$$  \hspace{1cm} (12)$$

This was used with the values $RH_{\text{min}} = 0.20$ and $RH_{\text{max}} = 0.40$. More on this in section 4.2.3.

All hydrometeor concentrations are removed below and above the cloud. While this is meant as a measure to make sure that clouds are not still existing below the cloud base or above the cloud top, another undesired effect is that precipitation below the cloud is completely removed during the initialization.

Within the cloud initialization process, temperatures are adjusted to conserve the virtual temperature inside the cloud. This is done to ensure that the hydrostatic dynamics in the model are not affected initially, but can later change. For example, this could ensure that no sudden changes in static stability occur (van der Veen, 2012). The temperature is adjusted in the
following way to ensure the conservation of the virtual temperature:

\[
T = T_v / \left( 1 + 0.608 q_m - q_w - q_i - q_r - q_s - q_g \right)
\]  \hspace{1cm} (13)

Here, \( T \) is the temperature, \( T_v \) is the virtual temperature, and \( q_w, q_i, q_r, q_s \) and \( q_g \) are the concentrations of cloud water, cloud ice, rain, snow and graupel respectively. Due to the mutual dependence between \( q_m \) and \( T \), there will also be adjustments to the specific humidity. This implies that the humidity according to Equation 9 and 10 should be updated when the temperature according Equation 13 is updated and vice versa. Therefore, these adjustments of temperature and humidity are repeated for a number of iterations, with a default of ten iterations unless specified otherwise. In addition, there is a limit with the possibility to prevent too large adjustments of specific humidity. The motivation is to avoid too large deviations from the balanced background model state, but the effect is not well documented.

2.6 HARMONIE-AROME cloud initialization results

An extended parallel experiment has been run for a three-month period during April to June 2017. This was done by Magnus Lindskog and Tomas Landelius at SMHI for the purpose of examining the potential of using cloud initialization for forecasts of solar energy. One of the parallel experiments was done using standard operational settings, and in the other, cloud initialization based on MESAN clouds was applied. At an early stage, it was seen that the experiment utilizing cloud initialization generated forecasts with more clouds than was produced when cloud initialization was not applied and also as compared with synoptic cloud observations. It seemed that too many clouds were generated with the cloud initialization applied with the MESAN cloud data, and therefore after one month of model integration, the cloud initialization experiment was restarted and replaced with a revised cloud initialization technique. The major revisions were (1) to only interpret MESAN clouds as clouds if they were thick enough, and (2) to calculate saturation water vapor relative to ice (and not water) in the cloud initialization procedure if cold enough. In Figure 3, verification of relative humidity forecasts for the operational reference run (CRL, red line), the original cloud initialization run (MES, blue line), and the revised version of the cloud initialization run (CLD, green line) are shown. Scores are for verification of total cloud cover against SYNOP cloud measurements over the entire area (3a), over Denmark (3b), over Norway (3c), and over Sweden (3d). The results reveal significant decreases in biases relative to SYNOP cloud measurements between the different parallel experiments and between different sub-areas of the domain. In terms of standard deviations, it seems that the cloud initialization has an effect up to a forecast range of approximately 12 h. A deeper understanding of the results would require a more detailed study of the MESAN data and the functionality of the cloud initialization.
procedure.

![Figure 3](image1.png)  
**Figure 3.** Standard deviation and bias of the verification of the three-dimensional model experiment against every SYNOP station in each respective location.

3 Methodology

3.1 Data used

The cloud data used in this project are from MESAN for the months April, May and June of the year 2017. This spring period was selected as spring typically has favorable conditions for the harnessing of solar energy, which ties together with the results in section 2.6. The area of which MESAN data is used is shown in Figure[4]
The gridded area covers the Scandinavian area. Not only the gridded MESAN products are used, but also the measurements used to produce the MESAN products. Over land, measurements come from a combination of SYNOP station data, satellite data, and a background model field. Over the sea is different as there are no SYNOP stations.

Satellite data in MESAN come from products from geostationary and polar-orbiting satellites. The products are based on the EUMETSAT (European Organization for the Exploitation of Meteorological Satellites) Nowcasting SAF (Satellite Application Facilities) and more detailed information about the products can be found at [http://www.nwcsaf.org](http://www.nwcsaf.org).

HARMONIE-AROME data comes from experiments run for the same period with cloud initialization during each data assimilation cycle, which will be referred to as MSGINIT, and without cloud initialization, referred to as control run (CRL). The area covered by HARMONIE-AROME is slightly larger than the area in Figure 4. In this study, a one-dimensional framework was also used in addition to the three-dimensional HARMONIE-AROME model system. More on this in section 3.3. Radiosonde measurements of temperature and humidity were used for evaluation of one-dimensional results.

### 3.2 Statistical methods

Other than the subjective methods used in this project, some statistical methods have been used to compare both the model runs, and the MESAN data with the input observational data. Python scripts have been used to implement these.

Two standard measures when examining many meteorological variables are the mean and the standard deviation. For any meteorological variable \( x \) with \( n \) measurements, the mean (\( \bar{x} \)) and standard deviation (\( \sigma \)) are calculated as:

\[
\bar{x} = \frac{1}{n} \sum_{i=1}^{n} x_i
\]

\[
\sigma = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} (x_i - \bar{x})^2}
\]
and standard deviation \((s)\) are defined as:

\[
\bar{x} = \frac{1}{n} \sum_{i=1}^{n} x_i \tag{14}
\]

\[
s = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} (x_i - \bar{x})^2} \tag{15}
\]

The mean is shown in Equation \((14)\) and the standard deviation in Equation \((15)\). The standard deviation shown here is an estimate of the true standard deviation, with the mean as an estimate of the expected value (Wilks, 2006). In this project, the standard deviation of the difference between observations and modelled values are examined.

Another useful tool for comparing two sets of data is the correlation coefficient \(r\). It is a value between -1 and 1, with 0 meaning no correlation between the two data sets, -1 meaning a perfect negative correlation, and 1 meaning a perfect positive correlation. For data on two variables, \(x\) and \(y\), with \(n\) measurements, it is given by:

\[
r = \frac{1}{n} \sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y}) \frac{1}{s_x s_y} \tag{16}
\]

Here, \(s_x\) and \(s_y\) are the standard deviations for \(x\) and \(y\). When looking at time series, this \(n\) is the total amount of time steps, and when looking at an area-average, \(n\) is the amount of measurement locations.

### 3.3 Analysis tools

Other than the previously mentioned methods, there were also tools used for producing results for studying the cloud initialization effect on one-dimensional cloud profiles. Following is a quick description of these tools.

- A tool to extract MESAN data from one particular part of interest was used. Cloud fraction data, as well as cloud top heights and cloud base heights were extracted and used for the stand-alone cloud initialization.

- A stand-alone version of the cloud initialization process, as described in section 2.5, involved extracting one-dimensional vertical column model profiles for one particular horizontal point of interest and applying modifications to these. The modified profiles were the specific humidity profile, the temperature profile, and the hydrometeor concentration profiles. These modifications included the insertion of extracted cloud data from MESAN. This stand-alone version reproduces the cloud initialization procedure in the three-dimensional model applied at each horizontal position.
• MUSC is a one-dimensional vertical column version of HARMONIE-AROME. This tool is useful for making idealized experiments where processes and changes can be studied on a vertical profile. Another useful aspect of such a tool is that the large-scale dynamics included in the three-dimensional version of HARMONIE-AROME can be excluded so as to only look at the processes of interest at a small scale. In this case, the vertical profiles of specific humidity, temperature and concentrations of hydrometeors from MUSC were studied. These profiles were studied inside and outside of the cloud layers with cloud initialization modifications according to section 2.5 of this paper. For comparison, one-dimensional profiles directly from the three-dimensional version of HARMONIE-AROME were extracted. This was done to investigate whether the profiles from MUSC and 3D HARMONIE-AROME were in agreement.

• The tools were used in a UNIX system framework and consisted of UNIX scripts and programs based on the FORTRAN programming language. For visualization of results obtained with the tools and statistical analyses, the Python programming language was used.

4 Results

4.1 Analysis of MESAN input cloud data

4.1.1 Data sources

Three sources of MESAN input data were analysed in the following section: the background model field (or the model run used as a first-guess in MESAN), the SYNOP station data and the satellite data. Mainly the geographic distribution and the area-averaged time series of cloud fractions were studied. The motivation for this study was to quality control the data, and to deepen the understanding of the cloud input data used for the cloud initialization technique.

4.1.2 Background model

The time series of the fraction of the MESAN area (see Figure 4) covered by clouds as estimated by MESAN is shown in Figure 5. Data is shown for every sixth hour, which is represented as one case, starting at 00 UTC during April 1. Figure 5a shows the cloud fraction series for all cases for MESAN (blue line) and a re-run of the background model used in MESAN (red line), and Figure 5b shows the difference between the MESAN data and the background model data. A re-run of the background model means that the model was run with the same settings and time as the background model field used in MESAN. Background model cloud cover is converted from a three-dimensional field to a two-dimensional field by assuming MRO of clouds from different layers of clouds as according to Equation 8. In 5a, it is seen that the MESAN cloud cover estimates are systematically higher than the corresponding background
model cloud cover. This could be due to other data sources in MESAN observing clouds that are not in the model or due to some systematic behavior in the MESAN procedure. Such a systematic behavior could be a smearing effect of the analysis system, for example. Looking at [5b] there are a few occasions, however, where the MESAN data shows lower cloud fraction values than the background model. The overall variation of cloud fraction in MESAN is in reasonably good agreement with the variation in the model. However, sometimes, like around case 275, agreement is less good.

![Graphs showing cloud cover differences](image)

**Figure 5.** Time series of cloud fractions of MESAN (blue line) and the background model (red line) in (a), and the difference in the mean in (b).

A map showing time-averaged cloud fraction differences between the background model and MESAN during the entire period examined and for the entire area is shown in Figure 6. Here, it is seen that over land, the differences between MESAN and the model are relatively small and in many places slightly negative with values between 0.0 and -0.1. The largest differences are positive and are seen over the sea, reaching over 0.1 in many places. Over-sea differences are a clear sign of discrepancies between satellite-observed and modelled cloud cover, where satellite images on average show more clouds than in the model. This is likely because this is the only source of measurements over the sea. The smaller differences between MESAN and the model over land areas may be due to the contribution from SYNOP data. It may however also be due to different systematic behaviors of satellite data and/or model data over land and sea respectively. Comparisons of MESAN with satellite data and SYNOP data respectively will help to deepen the understanding of the differences. Such comparisons are carried out in the following sections (4.1.3 and 4.1.4).
Figure 6. Time-averaged map of cloud fraction differences between MESAN and the background model for all cases.

Figure 7 shows the standard deviation of the difference between MESAN and the background model cloud fractions for the entire three-month measurement period. A large standard deviation would then mean a large variation of the MESAN and background model differences over time, likely due to problems in the model or in MESAN, for example, due to noise in instruments. Generally, larger standard deviations are seen over the sea, with the western edge showing the largest values. Over the sea, perhaps the satellite images cause more variations in MESAN. However, the high values shown around the western boundaries, as can also be seen in Figure 6, are most likely due to how LAM, like HARMONIE-AROME used here, handle the lateral boundary conditions. This handling of the boundary conditions here appears to cause underestimations of clouds, as has been shown by Belušić, Lindestedt and Lind (2018). Over Norway, standard deviations are lower than over Sweden and Finland, which means smaller fluctuations in differences in MESAN and model are found in that area. SYNOP station density being lower in the mountainous areas, differences in the quality of the measurement data, or clouds being easier to produce due to orographic forcing could be possible explanations. The existence of these standard deviations between MESAN and the model points at a potential to use MESAN data to correct the model cloud forecasts.
Figure 7. Time-averaged map of cloud fraction difference standard deviation between MESAN and the background model for all cases.

In Figure 8, a linear fit of the background data and the MESAN data are shown, and also the correlation coefficient between the two data sources is displayed. Here, there is a positive bias in the MESAN data, meaning higher values than the background model data. The correlation coefficient was calculated as approximately 0.87. There is a visible difference between the datasets, which is caused by the additional measurement data sources in MESAN. Also, there appears to be larger differences between MESAN and the model for lower cloud fractions, as the linear fit is slightly tilted from the perfect correlation. However, this could be due to fewer measurements of lower cloud fractions. The data points are quite scattered as well, especially at lower cloud fractions, which means that there are significant deviations from a perfect correlation.
Figure 8. Correlation between MESAN (y-axis) and the background model (x-axis) for all cases. The yellow line is a linear fit of the data, and the black line is the linear fit that would be expected of a perfect linear correlation.

4.1.3 Satellite data

For examining the relation between MESAN and satellite data, Figure 9 shows a time series of the fraction of a limited area that is covered by clouds. The time series is for each sixth hour during the three-month period. This area is between 55° and 71° latitude, and −4° and 34° longitude as shown by Figure 10. The MESAN data (middle blue line), satellite data (upper green line), and the background model data (lower red line) are displayed for every sixth hour. Compared to the two other data types, the satellite data appears to show significantly more clouds. Overestimations in the satellite data might be the cause, which might lead to higher values in the MESAN product as well. To the extent that geostationary satellite data is used, some overestimations may be due to the steep viewing angle of the satellite as it views northern Europe. Other causes could be misinterpretations when interpreting the information from the satellite data, and underestimations by the SYNOP measurements. An example analysing the difference between satellite images and MESAN for one particular case can be found in section 4.1.4.
**Figure 9.** Time series of cloud fractions of the background model (red line), MESAN (blue line) and satellite data (green line).

**Figure 10.** Map of the area of over which satellite data and MESAN data are compared. The area is contained within the MESAN area shown in Figure 4. This is from an example of interpreted satellite imagery.
A linear fit, and the correlation coefficient, of the satellite to the MESAN data is seen in Figure 11. What can be seen is that there is indeed a negative bias, where satellite data values are higher in general than the MESAN data values. The correlation coefficient is approximately 0.78. This lower coefficient than the background model is caused by the data here being even more scattered than was the case when comparing MESAN with the background model.

![Correlation between MESAN (y-axis) and the satellite data (x-axis) for all cases. Again, the yellow line is a linear fit to the data, and the black line represents what would be expected of a perfect linear correlation.](image)

*Figure 11.* Correlation between MESAN (y-axis) and the satellite data (x-axis) for all cases. Again, the yellow line is a linear fit to the data, and the black line represents what would be expected of a perfect linear correlation.

### 4.1.4 Synoptic station data

Cloud fraction time series for MESAN and synoptic weather stations for the three-month period are seen in Figure 12. The MESAN and SYNOP data are compared for every third hour, starting on April 1, leading to more cases than displayed in the model and the satellite cases. In Figure 12a, the cloud fraction time series for MESAN (blue line) and SYNOP (red line) is shown for all cases. In 12b, the cloud fraction difference, averaged over all SYNOP stations within the MESAN area, between MESAN and SYNOP for all cases is seen. MESAN data for the closest grid-points to each SYNOP point were used. The time series 12a shows how the MESAN and SYNOP data follow each other very closely. However, the MESAN data always have slightly larger values of cloud fraction than the SYNOP data, which is especially clear in 12b, where the differences are always positive. Most of the time, the cloud fraction differences were under 0.10, but for certain cases, larger differences were found. The overall positive bias of the
MESAN data relative to the SYNOP data could be due to horizontal and vertical limitations of the SYNOP measurements in finding the correct cloud cover, which was instead found by, or perhaps overestimated by the model- and the satellite data. Horizontal limitations may become a problem when there are small-scale cloud patterns that are missed by the station network.

(a) Cloud fraction time series of MESAN (blue line) and the SYNOP data (red line). (b) Time series of the differences between the cloud fractions MESAN and the SYNOP data.

Figure 12. Time series of mean cloud fractions of the MESAN (blue) and the SYNOP data (red line) in (a), and the differences in (b).

The standard deviation of the differences between MESAN and SYNOP are displayed in Figure 13. Cases with large standard deviations mean that the non-systematic part of the difference between the SYNOP data and the MESAN data is large, when taking all observations in the domain into account. What is seen is that there is a baseline standard deviation of around 0.20, which means that the differences between the cloud fraction differences in the stations typically stay around that level. In the beginning of the period, there are larger standard deviations, with some peaks reaching over 0.40. Only a few peaks reach over 0.35 after that point. This all means that, while the SYNOP data is used in MESAN, there are some places where they might be more outweighed by other MESAN input data. Another reason might be that in cases with small-scale variations nearby stations might provide contradictory information for how to assign a cloud cover value for one grid-point.
Figure 13. Standard deviation of the difference between cloud fractions in MESAN and the SYNOP data for all cases.

Figure 14 shows the time-averaged cloud fraction differences between MESAN and SYNOP for every available station for the three-month period. Each station is marked by a dot with color depending on the cloud fraction difference over that station. Over Sweden and Finland, mainly large positive differences were seen, unlike Norway and most of the Baltic countries where the differences were small. Spatial variations could be caused by the type of synoptic cloud measurement used at the station, and on whether the stations were manual or automatic. Only a few of the stations in Sweden and Finland are manual. Norway has a larger amount of manual cloud observations. This means that Sweden and Finland are more affected by the limitations of the automatic SYNOP stations, such as cloud bases higher up than 7600 m being missed. Also, one station appears to give poor quality data over the eastern coast of Denmark, as shown by the blue dot. In general, what is seen is that SYNOP station data appears to underestimate cloud cover as compared with MESAN, especially over Sweden and Finland.
As for the previous MESAN input datasets, the linear fit between MESAN and SYNOP is seen in Figure 15. Every value of MESAN is seen as higher than in SYNOP. This points to a clear negative bias in the SYNOP data. The correlation coefficient is approximately 0.95, a very high value. Compared to the other data sources, the data are much less scattered, giving this higher correlation coefficient. This implies that the SYNOP data have a large effect in the areas where the stations can be found.

Figure 14. Time-averaged map of cloud fraction differences between MESAN and the SYNOP for all cases.
Figure 15. Correlation between MESAN (y-axis) and the SYNOP data (x-axis) for all cases. The yellow line is the linear fit of the data, and the black line is what would be expected of a perfect linear correlation.

4.1.5 Case studies

Some of the cases in Figure 5 have been analyzed further. Figure 16 shows two such cases: 16a is from April 25 at 18 UTC, which corresponds to the peak around case 100 in Figure 5b), and 16b is from May 1 at 12 UTC, which corresponds to negative values of the difference near case 125 in Figure 5b. Thus, 16a displays a case where MESAN shows higher cloud fractions than the background model, and 16b displays a case where model cloud fractions may exceed the MESAN values. In 16a, most places with higher values in MESAN are found around the southern parts of the Baltic sea, the North Sea, and the Norwegian Sea. Some positive differences are also seen in Norway and some negative differences in the northernmost parts. As MESAN relies on satellite images over the sea, these over-sea differences are likely due to the satellite data. Some of the land differences could also be the addition of the synoptic weather station data. For 16b, some positive differences remain around the Norwegian Sea, but more negative differences can be found. A spot with large negative differences can be found around the eastern part of Denmark, and another south of the positive differences over the Norwegian Sea. Note as well the overall negative differences over land areas, probably related to SYNOP data.
Figure 16. Cloud fraction differences between MESAN and the background model for April 25 (a), and for May 1 (b).

Figure 17 and 18 display the cloud fractions for the background model field and in MESAN for the case corresponding to Figure 16a and 16b respectively. The cloud field in Figure 17b is more smeared than in Figure 17a and there are indeed more clouds, for example in the northwestern part of the domain. As for the case in Figure 16b, comparing Figure 18a and 18b it is obvious that over sea, MESAN and the background model show very different cloud patterns. In addition, over land areas in the middle of Sweden and Norway, less clouds are found in MESAN as compared with the background model.

Figure 17. Cloud fractions in the background model (a) and MESAN (b) for the case in Figure 16a.
Figure 18. Cloud fractions in the background model (a) and MESAN (b) for the case in Figure 16b.

For comparing MESAN and satellite data, a case from April 17 2017 at 12 UTC has been analysed. Figure 19 shows the cloud fraction from MESAN in 19a and from the satellite data in 19b, while Figure 20 shows the cloud thickness from MESAN in 20a and from the satellite data in 20b. The cloud thickness is defined as the difference between the cloud top height and the cloud base height. Also, the cloud base and top heights are found in Figure 21 and 22 respectively. Comparing 19a and 19b, the MESAN cloud fractions appear smudged compared to the satellite cloud fractions. More fine-detailed cloud patterns appear discernible in the satellite data. However, the satellite data does not differentiate between intermediate cloud fraction numbers, whereas it instead shows cloud fractions of 1.0 almost everywhere it finds clouds. This is more discernible in the MESAN data, although some of the structures might be caused by the data interpolation smudging in MESAN. The effect of this interpolation may be clearer in Figure 20a. Here, the MESAN data appears to show patches of clouds with significant thicknesses in accordance with the satellite data in 20b, but it is clear that many of the fine details have been smoothed out through interpolation. Figure 20b shows more finer cloud structures, although some structures look jagged, such as off the west coast of Norway and in southern Finland. Lower resolution could be one cause of the oddities in these regions. The cloud base heights in Figure 21a and 21b are similar to each other, although the MESAN cloud bases are higher in some parts, such as a spot with cloud bases of over 3000 m over northern Sweden. In the cloud top data, comparing Figure 22a with 22b, the jagged structures in the satellite cloud thickness map are present.
Figure 19. Cloud fractions in MESAN (a) and satellite data (b) for April 17 2017 at 12 UTC.

Figure 20. Cloud thickness (m) in MESAN (a) and satellite data (b) for April 17 2017 at 12 UTC.
Comparing Figure 23, which is a satellite overview image, with Figures 19-22 reveals several interesting things. First of all, the overall cloud situation is reasonably well captured by both MESAN and the satellite product. However, both the MESAN and the satellite product most likely overestimate the cloud amounts when comparing Figure 19 with 23. Small-scale variations are better represented by the satellite product. Another thing is that from the satellite image, one can expect two layers of clouds over Southern Finland. In the MESAN and satellite products these are represented as thick clouds. For this particular case, the effect of SYNOP measurements reducing cloud amounts over land as previously seen was not very obvious.

If clouds categorized by the satellite product as fractional clouds are removed, a more realistic result is produced. Fractional clouds include both very small-scale clouds and thin clouds.
Figure 24 shows what removing fractional clouds does to a satellite product. The cloud cover becomes more what would be expected from an interpretation of Figure 23, with a lot more cloud-free locations than in presented in Figure 19b. This further displays the difficulties with interpreting satellite imagery. It should be mentioned that the definition of a cloud is a bit vague, not taking the concentration of water and/or ice particles into account. Therefore, the inclusion of fractional clouds in the satellite product is not always wrong. However, for our purposes, it does not seem suitable to include this fractional cloud category.

Figure 23. Satellite RGB-image for April 17 2017 at 12 UTC.

Figure 24. The satellite product with fractional clouds (left) and with no fractional clouds (right) for April 17 2017 at 12 UTC.

Creating initial model fields using MESAN and the satellite products yields Figure 25, with using MESAN in Figure 25a and using the satellite product in Figure 25b. In Figure 25a
the CLD experiment, where thin clouds were removed, is used for the initial model field. The MESAN cloud field shows significantly smaller cloud amounts, which is especially visible over sea. Although 25b shows too much cloudiness, the cloud field in 25a appears to miss quite a few of the smaller-scale patterns visible in Figure 23.

**Figure 25.** Initial model cloud fraction fields from MESAN (a) and the satellite product (b).

**Figure 26.** The cloud fraction field that the initial model cloud fraction field in Figure 25a is based on.
4.1.6 Summary of the MESAN cloud data analysis

This section of the results can be summarized to highlight the most interesting conclusions in the following way:

- There is a positive bias in the area-averaged MESAN cloud fraction data relative to the background model data.
- Area-averaged satellite cloud fractions are almost always higher than in MESAN for the same area.
- There is a positive bias in the MESAN cloud fraction data relative to the SYNOP data.
- There are positive cloud fraction differences between MESAN and the background model over sea, and mostly negative differences over land. This is most likely due to overestimations of clouds by satellites that provide the only measurements over sea, and by underestimations of clouds by SYNOP measurements influencing MESAN over land. A case study indicated that the satellite overestimation is due to inclusion of the category fractional clouds in the satellite product.
- Larger systematic positive differences in cloud fractions between MESAN and SYNOP are seen over Sweden and Finland than over Norway.
- Standard deviations and correlations between MESAN and the background data, as well as case studies, indicate that there is room for modifying the background cloud fractions by using MESAN data.

4.2 Cloud initialization profiles

4.2.1 Example of modified profiles through cloud initialization

Figure 27 shows an example of how cloud initialization may change the specific humidity profile in a vertical column in HARMONIE-AROME. This case is from Uppsala 8 April 2017 at 12 UTC. An artificial cloud has been added to clearly display the effects of the initialization. This shows that the specific humidity at saturation, calculated through the model temperature, is significantly higher than the specific humidity in the model, and thus the humidity change is significant. Below the cloud base, and above the cloud top, the specific humidity is also significantly reduced (down to $CCC \cdot QS$, shown as the green dotted line). This leads to a rather drastic change in specific humidity just below the cloud base. Figure 28 shows the modified temperature profile. Only a slight change in temperature is seen, which is most likely from the changes required to keep the virtual temperature constant in accordance with the
cloud initialization description in section 2.5. In this experiment, a $CCC$ in accordance with Equation 12 and $RH_{min}$ and $RH_{max}$ values of 0.20 and 0.40 were used. The default number of 10 iterations was used.

**Figure 27.** Example of a modified one-dimensional specific humidity profile from a vertical column over a grid-point in HARMONIE-AROME over Uppsala during 8 April 2017. A cloud has been ingested between vertical levels 53 and 32. The blue line gives the HARMONIE-AROME specific humidity profile for all vertical layers in the model before the cloud initialization, and the red dashed line gives the modified specific humidity after the cloud initialization. Saturation specific humidity is shown as the black line, and the green dotted line is the saturation specific humidity multiplied with $CCC$ (see section 2.5 for an explanation of this parameter). Also, the cloud base and top are shown by the black horizontal lines.
Figure 28. Example of a modified one-dimensional temperature profile from a vertical column over a grid-point in HARMONIE-AROME over Uppsala during 8 April 2017. A cloud has been ingested between vertical levels 53 and 32. The blue line gives the HARMONIE-AROME temperature profile for all vertical layers in the model before the cloud initialization, and the red dashed line gives the modified temperatures after the cloud initialization. Also, the cloud base and top are shown by the black horizontal lines.

To illustrate how the concentrations of hydrometeors in the vertical column may change, Figure 29 shows profiles of cloud ice and snow over the same time and area as previous profiles. In Figure 29a, the HARMONIE-AROME profile (blue line) displays some concentrations of cloud ice above where the virtual cloud is. This is then removed, as shown by the modified profile (red dashed line). The same thing can be seen in Figure 29b, but some of the snow is present inside the cloud, which is then preserved.

All of these display the overall behavior of the cloud initialization: cloud top, cloud base, and cloud fraction data are taken from MESAN (except for this example where an artificial cloud was added), which are then used to modify the vertical profiles at each horizontal position. The present profiles in HARMONIE-AROME may then be changed significantly, and below and above the MESAN cloud, the humidity undergoes a significant decrease and the hydrometeors are removed. Hydrometeors are not added inside the cloud, and are instead expected to be created in the model forecast.
Figure 29. Example of modified one-dimensional cloud ice (a) and snow profiles (b) from a vertical column over a grid-point in HARMONIE-AROME over Uppsala during 8 April 2017. A cloud has been ingested between vertical levels 53 and 32. The blue lines give the HARMONIE-AROME hydrometeor concentration profiles for all vertical layers in the model before the cloud initialization, and the red dashed lines give the modified hydrometeor concentrations after the cloud initialization. Also, the cloud bases and tops are shown by the black squares.

4.2.2 Number of iterations in the cloud initialization process

This section shows some results displaying the effects of varying the amounts of iterations mentioned in section 2.5 of this paper, the method of which the purpose was to take into account the mutual dependence of the specific humidity updates according to Equation 9 and 10 and the temperature updates according to Equation 13.

It was mentioned in section 2.5 that there is a limit in specific humidity changes imposed to avoid too large deviations from the balanced model background state. This experiment revealed that the limit check was in this HARMONIE-AROME implementation not applied to the final result after all iterations, but to the intermediate result after each iteration. This implies that the limit check does not work as intended, and will not have an effect if a large enough number of iterations is used, as the desired profile according to Equation 9 and 10 will still be reached even if it is larger than the assigned limit. The effect of this is displayed in Figure 30, where the same humidity profile as in Figure 27 is used, but with 8, 6, 4 and 2 iterations instead of the default 10. For only two iterations, due to the limit in change of specific humidity, \( q_s \) and \( q_s \cdot CCC \) have not been reached by the modified profile inside and outside the cloud respectively. For 4 iterations, the cloud profile is corrected as intended inside and above the cloud, but below the cloud, where a drastic change in specific humidity is meant to happen, the desired profile has not yet been reached. At 6 iterations, the profile looks as desired, and there is no discernable difference to 8 iterations (both upper profiles). Without this limited change in specific humidity, the profile would immediately have been reached.
Figure 30. Modified one-dimensional specific humidity profiles from a grid-point in HARMONIE-AROME over Uppsala during 8 April 2017. A cloud has been ingested between vertical levels 53 and 32. From left to right, top to bottom: 8, 6, 4 and 2 iterations are used. The blue line gives the HARMONIE-AROME specific humidity profile for all vertical layers in the model before the cloud initialization, and the red dashed line gives the modified specific humidity after the cloud initialization. Saturation specific humidity is shown as the black line, and the green dotted line is the saturation specific humidity multiplied with $\text{CCC}$ (see section 2.5 for an explanation of this parameter). Also, the cloud base and top are shown by the black horizontal lines.

Figure 31 shows profiles of specific humidity and temperature after the cloud initialization process in Figure 31a and 31b respectively. The limitations in specific humidity change have been turned off in this case. Only inside the cloud, just above the cloud base, can a slight difference between the two be seen. This difference between the two profiles is a maximum of approximately 8% as compared to the difference between the one iteration profile and the original profile. In Figure 31b, the temperature profile is seen. Here, the two profiles are close to each other. These results suggest that the use of several iterations only has a minor effect.
Figure 31. Modified one-dimensional profiles of specific humidity (a) and temperature (b) from a grid-point in HARMONIE-AROME over the Norwegian Sea during 15 June 2017. The blue line is the original profile before cloud initialization, the red (dashed in (a)) line is the modified profile with only one iteration, and the magenta dashed line is this profile with ten iterations.

In summary, it seems that the limit check does not work as intended, and the number of iterations used in the default settings might be imperfect. If the limit check is not used or applied to the final result, it is seen that the change due to the mutual dependence between the humidity and the temperature is small. Therefore, a smaller number of iterations could be used in the future if the limit check is removed or is applied only to the final result.

4.2.3 Sensitivity to assumed critical relative humidity profile

Initial experiments with the one-dimensional cloud initialization model revealed some differences as compared with the profiles from the three-dimensional modelling system. One such difference was the assumed critical relative humidity profiles. Comparing the effect of this difference will serve as a sensitivity study. Previously, Equation 12 was used for producing the results in section 4.2. Going forward, Equation 11 will be used in section 4.3, as it better represents realistic critical relative humidity profiles. Also, the values for $RH_{\text{max}}$ and $RH_{\text{min}}$ previously used were 0.40 and 0.20 respectively, and these were useful for demonstrations of the cloud initialization process below and above the cloud layer. In section 4.3, the values $RH_{\text{max}} = 0.65$ and $RH_{\text{min}} = 0.58$ from the three-dimensional system will be used. Figure 32 shows a comparison of the two different $CCC$ profiles with the previously used equation and the currently used equation. The blue line is the same $CCC$ as in Figure 2 and the red line is $CCC$ with Equation 12. Changing to the new $CCC$ turns the profile around, giving a minimum in $CCC$ somewhere above the mid-troposphere, and with the new $RH_{\text{max}}$ and $RH_{\text{min}}$, the changes in $CCC$ with height are smaller.

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Figure 32. Vertical profiles of CCC with Equation 11 (blue line) and 12 (red line), with previously given values of $RH_{\text{max}}$ and $RH_{\text{min}}$.

Figure 33 shows an example from Gotland June 7 2017, where in Figure 33a, the specific humidity profile using the old CCC is compared with radiosonde measurements, and in Figure 33b, the profile with the old CCC is compared with the profile with the new CCC.

What is seen in Figure 33a is the original profile as the blue lines, and the cloud initialized profiles as the red lines. The profiles in the previous results, and the run here labeled as MSGINIT have had cloud initialization done every third hour. This means that the original profile shown as the blue line had cloud initialization applied to it three hours prior. An experiment completely without prior cloud initialization was added, and is shown as the blue and red dashed lines (denoted by crl for control run). Corresponding radiosonde data is shown as the magenta line. Throughout most of the cloud layer, the radiosonde specific humidity is slightly below that of the saturation specific humidity calculated from both the control run and the MSGINIT run. Only near the cloud base and at around 500 hPa-600 hPa do these seem to coincide. It would seem from the radiosonde data that multiple layers of clouds are present at these two vertical levels. The weakness with the cloud initialization would then be that this is instead represented as one full layer of clouds from the MESAN cloud base to the cloud top, creating more clouds and moisture than what seems to be present in the radiosonde observation. From the cloud base up to slightly above 800 hPa, the specific humidity of the original control run is higher than the specific humidity of the original MSGINIT run, and also closer to the
radiosonde data there. However, above this point, the original MSGINIT humidity is slightly higher than the original control run humidity, and is also then closer to the radiosonde data for most levels. Below the cloud base, the original control run specific humidity is higher than the MSGINIT original run, also closer to the radiosonde data.

Figure 33b shows the same profile as in Figure 33a, with the old and new CCC (magenta dashed line and red dashed line respectively), and without the radiosonde profile and the control run profile. Through the new CCC, the modifications made through the cloud initialization are smaller, and the only significant change in humidity is just below the cloud, where there is still a discontinuity. In newer versions of this cloud initialization method, perhaps a smoother vertical change in humidity below the cloud base could be obtained, but these new results are still much more reasonable than with the old CCC, and a better correspondence with the radiosonde profile is observed. The conclusion is that, although ideal for demonstration of the general effects of the cloud initialization process by exaggerating the effects, the settings in the three-dimensional model produce more realistic results for this case study according to the radiosonde observations, and will from now on be used.

4.2.4 Sensitivity to the saturation specific humidity

An analysis of the saturation specific humidity with respect to water and ice was carried out. A vertical temperature profile over Gothenburg 24 April 2017 (chosen because the temperatures
were low at this location for this time) was used to calculate the specific humidities at saturation with respect to water and ice. This was done using the following formulas.

\[
\ln e_{sw} = 55.281723 - \frac{6808.475}{T} - 5.088336 \ln T
\]  

(17)

\[
\ln e_{si} = 24.294459 - \frac{6141.581}{T}
\]  

(18)

\[
q_s = \frac{\epsilon e_s}{p - (1 - \epsilon)e_s}
\]  

(19)

Equation \[17\] is the Magnus formula for saturation vapor pressure with respect to water \((e_{sw})\), where \(T\) is the temperature in Kelvin. Equation \[18\] is a similar formula for saturation vapor pressure with respect to ice, and \[19\] is how the specific humidity is calculated from these with \(\epsilon\) being the ratio between the gas constant for dry air and the gas constant for water vapor, and \(p\) being the atmospheric pressure.

Figure 34 contains the produced results for the vertical levels 15-27 in this case, where temperatures were below 253 K. The red lines show the saturation specific humidity \((q_s)\) with respect to ice, and the blue lines with respect to water. The dashed lines are the saturation specific humidity, and the full lines are the \(q_s\) multiplied with the \(CCC\) (in accordance with Equation \[11\]) for this case. As can be seen, \(q_s\) is always slightly larger than with respect to ice.

If above the clouds, the modified profile would be equal to the full lines. In the case of using \(q_s\) with respect to water, the modified profile would then overlap with the \(q_s\) with respect to ice (compare the dashed red line with the blue line) at the higher levels, at around level 18 and above in this case. This could perhaps lead to unwanted formations of high clouds. The effect will increase with larger values of \(RH_{min}\) and \(RH_{max}\) contained within the formulation of \(CCC\). Thus, this indicates that using \(q_s\) with respect to ice at higher levels, where temperatures are low, is prudent.
4.3 Cloud initialization lifetime

When using MUSC and replacing the original model humidity profile with the cloud initialized profile, there is an option to change which profile should be used as a forcing profile. What this means is that an initial profile is set, which in this case would be the cloud initialized profile, and then a profile that the initial profile should tend towards after being integrated forward in time is set. The same can be done for the temperature. This allows for simulation of situations where the large-scale weather patterns may differ from the MESAN-based measurements. In addition to this forcing, the profile is changed due to model physics acting on the profile as MUSC is integrated forward in time.

4.3.1 Artificial cloud simulation and time-scales

This section involves a case from Tierp, just about 100 km north of Stockholm, May 5 2017 at 00 UTC, during a clear night. Two cases were studied: one with an artificial cloud with a cloud base at 100 m and a cloud top at 2 km, and another with an artificial cloud with a cloud base at 6 km and a cloud top at 9 km. The first one represents a case with low clouds mostly within the planetary boundary layer, where a lot of turbulent mixing occurs during the day, and the second
one represents a case with high clouds in the free atmosphere. The MUSC model was integrated 12 h forward in time. In Figure 35, the first case with low clouds are studied. There are two profiles integrated forward in time in Figure 35a: the original, non-cloud-initialized profile, shown as the dashed lines (ori), and the cloud initialized profiles shown as the filled lines (ini). Forecast times of 0 h, 1 h, 2 h, 3 h, 6 h, and 12 h. Both of these profiles use their own profiles as forcing profiles. The same cloud initialized profiles (filled lines) are shown in Figure 35b as the filled lines, but the dashed lines represent the case with a cloud initialized initial profile, and the original profile from Figure 35a as the forcing profile. Below vertical level 50, the cloud initialized profile in Figure 35a appears to vertically mix with each hour as the change in humidity adapts to the rest of the physics in the model. After 3 h (yellow filled line), the profile has become visibly more continuous, but there is still a large decrease of humidity below the cloud base. However, after 6 h (red filled line), the entire humidity profile has smoothed out significantly, and the decrease in humidity below the cloud is smaller. After integrating 12 h forward in time (pink filled line), the humidity profile is mostly constant with height, or almost decreasing slightly with height, within the planetary boundary layer, as expected from the large vertical mixing during the daytime. This boundary layer structure is more in accordance with the original profile. There is, after 12 h of integration, however, still a large difference between the original profile and the cloud initialization profile. Furthermore, note that above level 50, the model physics do not change the profiles that are supported by the forcing. In Figure 35b, the differences between the dashed and the full lines are due to different forcing applied. At the start, both profiles are aligned and equal to the initialized profile. However, the forcing is different. "If" stands for initialized profile forcing and "of" stands for original profile forcing. Note the large sensitivity of the MUSC results to the forcing profile applied. If forcing towards the original profile is applied (dashed lines), already after roughly 3 h, the initialized profile has become very similar to the original profile (used as forcing). That is, Figure 35b reveals the importance of the applied forcing profile.

One setting that was also adjustable was the time scale at which the initial profile tends towards the forcing profile. In Figure 35, the forcing time scale was set to 1 h. For comparison of this to a forcing time scale of 3 h, Figure 36 shows the same case as Figure 35b but with a 3 h forcing time scale. Here, it takes over 6 h for the original profile to be reached (the dashed lines), unlike the 3 h when a forcing time scale of 1 h is used. After 12 h, they are identical. As for the profiles with initial forcing (full lines), the profile after 6 h is not as vertically mixed as in Figure 35b. This vertical mixing of the humidity profile takes more time. Also, after 12 h, comparing the pink line in Figure 35b and 36, they look slightly different. In Figure 36, the profile decreases with height in the vertical, whereas there is a slight increase in humidity with height in Figure 35b within the lowest ten levels. The shape of the profile in Figure 36 is in slightly better accordance with the original profile, when the original profile is used as forcing.
Figure 35. Specific humidity profiles from Tierp May 09 2017 at 00 UTC with an artifical low cloud. In (a), the original model profile ("ini", dashed lines) and the cloud initialized profile with cloud initialized forcing ("ori", full lines) are seen. In (b), both profiles are cloud initialized, but one with cloud initialized forcing ("if", full lines), and one with original forcing ("of", dashed lines). The dark blue lines are the initial profiles, and the light blue, green, yellow, red, and pink lines are forecasts with time steps of 1 h, 2 h, 3 h, 6 h, and 12 h. A forcing time scale of 1 h was used.

Figure 36. Specific humidity profiles from Tierp May 09 2017 at 00 UTC with an artifical low cloud. Both profiles are cloud initialized, but one with cloud initialized forcing ("ini", full lines), and one with original forcing ("ori", dashed lines). The dark blue lines are the initial profiles, and the light blue, green, yellow, red, and pink line are the forecasts with time steps of 1 h, 2 h, 3 h, 6 h, and 12 h. A forcing time scale of 3 h was used.
Figure 37 contains the same case as Figure 35, but with cloud water concentrations. Figure 37a and 37b look identical. The reason for this is that the initial profile shows no cloud water at all, and when the forcing is such that there is supposed to be a cloud present, cloud water is produced as seen by the filled lines in Figure 37a and 37b. However, if the forcing dictates that no cloud is present, no cloud water is produced as seen by the dashed lines that are all at $0.0 \text{ kg kg}^{-1}$ in Figure 37b. It can be seen that already after $1 \text{ h}$ of model integration, significant amounts of cloud water is produced in the case of initial forcing. The amounts are as large as after $6 \text{ h}$ or $12 \text{ h}$ of model integration, therefore no spin-up problem of clouds is evident. Cloud water is produced at a time scale of less than $1 \text{ h}$, according to Figure 37.

![Cloud water profiles from Tierp May 09 2017 at 00 UTC with an artificial low cloud.](image)

(a) **Figure 37.** Cloud water profiles from Tierp May 09 2017 at 00 UTC with an artificial low cloud. In (a), the original model profile ("ini", dashed lines) and the cloud initialized profile with cloud initialized forcing ("ori", full lines) are seen. In (b), both profiles are cloud initialized, but one with cloud initialized forcing ("if", full lines), and one with original forcing ("of", dashed lines). The dark blue lines are the initial profiles, and the light blue, green, yellow, red, and pink lines are forecasts with time steps of $1 \text{ h}$, $2 \text{ h}$, $3 \text{ h}$, $6 \text{ h}$, and $12 \text{ h}$. A forcing time scale of $1 \text{ h}$ was used.

The specific humidity profiles in the second case are studied in Figure 38, with the same types of lines and coloring as in Figure 35. In this case, the cloud base is just below vertical level 20. The cloud is $3 \text{ km}$ thick, which is even thicker than in the first case with the low cloud, but due to the vertical model resolution being higher near the surface, the cloud only spans a few vertical levels. What can be seen in Figure 38a is that the changes due to the cloud initialization are intact even after $12 \text{ h}$. This is unlike in Figure 38b (dashed lines), where it takes $1 \text{ h}$ to $2 \text{ h}$ to be back to the original profile due to the forcing. The interesting difference between Figure 35a and Figure 38a is that while in the case of the low clouds, the profile is vertically mixed after a while, in the case of the high clouds, this does not occur during the $12 \text{ h}$ model integration, if forcing from the initialized model profile is used. Most likely, this is due
to limited vertical mixing in the free atmosphere, and these results show an interesting effect on the processes affecting the cloud initialization on different heights. At higher vertical levels, the large scale forcing is more important, and at lower levels, model physics play an important role.

![Figure 38](image.png)

**Figure 38.** Specific humidity profiles from Tierp May 09 2017 at 00 UTC with an artificial high cloud. In (a), the original model profile (“ori”, dashed lines) and the cloud initialized profile with cloud initialized forcing (“ori”, full lines) are seen. In (b), both profiles are cloud initialized, but one with cloud initialized forcing (“if”, full lines), and one with original forcing (“of”, dashed lines). The dark blue lines are the initial profiles, and the light blue, green, yellow, red, and pink lines are forecasts with time steps of 1 h, 2 h, 3 h, 6 h, and 12 h. A forcing time scale of 1 h was used.

### 4.3.2 Comparing MUSC and results from the three-dimensional model

Results from artificial cloud case studies with MUSC indicate that there may be differences in how long cloud initialization changes remain depending on the vertical level. Overall, the time scale of how long the initial state modifications remain is of the order of 6 h-12 h. However, there are uncertainties regarding what forcing profile and forcing time scale are appropriate to use. If the large scale situation is in accordance with the original profile, that is appropriate to use, but if the large scale situation is considerably changed by the cloud initialization the initialized profile is preferable to use. Regardless of what profile is used, there are uncertainties regarding forcing time scales. Comparison of MUSC results with results from the three-dimensional model may provide some guidance.

Two cases with clouds on two different heights were studied. In both cases, the cloud initialized profiles were used as starting profiles, and a 1 h forcing time scale was used. However, in the first case, the original profile was used as forcing profile, while in case 2, the initial profile was used as forcing profile. One-dimensional profiles from the three-dimensional version of HARMONIE-AROME, with cloud initialization applied, were also used for comparison.
The first case comes from the east coast of Sweden, 80 km northeast of Stockholm, during April 4 2017 at 00 UTC in Figure 39. Figure 39a is when MUSC is used, and Figure 39b is the corresponding profiles from the three-dimensional model. At this location and time, the MESAN data showed a cloud base height of 50 m and a cloud top height of approximately 2 km. This is classified as a low cloud. The initial specific humidity profile in Figure 39a starts of with a significant increase with respect to the original profile (not shown here). After around 3 h, the original profile has been reached. Within the boundary layer, which is comprised of the nearest vertical levels to the surface, the vertical mixing appears to keep the humidity relatively constant with height, even during the nightly hours. This could be one of the reasons why the profile smooths out each hour, but the forcing is also important. According to the three-dimensional model in Figure 39b that shows the cloud initialized profile integrated forward in time, where the forcings are different, the cloud initialization induced changes remains for a longer time. The humidity changes inside the cloud appear to remain for at least the first 3 h. After 6 h, the MUSC results and the three-dimensional model results are rather similar. Most likely, the largest differences between Figure 39a and 39b are due to the forcings. The effects of the cloud initialization on the specific humidity appear to last for over 3 h. It seems, however, that forcing with the control profile was appropriate here, but perhaps a forcing time scale of 3 h would have resulted in a better correspondence with results from the three-dimensional model.

![Vertical specific humidity profile](image1)

**Figure 39.** Specific humidity profiles from the east coast of Sweden April 4 2017 at 00 UTC. Low clouds were present at the time. In (a), the MUSC results are shown with original forcing and a forcing time scale of 1 h, and (b) shows the results from the three-dimensional model. The dark blue lines are the initial profiles, and the light blue, green, yellow, red, and pink lines are forecasts with time steps of 1 h, 2 h, 3 h, 6 h, and 12 h.

For the second case, clouds above the boundary layer with a cloud base height of 2 km and a cloud top height of 6.25 km were studied. This case is from Karlstad in Sweden April 28 2017 at 12 UTC. Again, Figure 40a and 41a is when MUSC is used, and Figure 40a and 41b...
are results from the three-dimensional model.

Note from Figure 40 that the initial cloud profile remain much longer in MUSC than in the three-dimensional model results. It seems that it is not appropriate to use the initialized cloud profiles as forcing profiles as well. This is also supported by Figure 41 which shows the corresponding snow profiles. While the three-dimensional model snow amounts are reduced significantly after 3 h, the same is not the case for the MUSC results, where the initialized state based forcing supports higher snow amounts remaining for a longer time.

From these case studies, it seems like using a 3 h forcing time scale and the original model profile forcing would be a good choice for reproducing three-dimensional model results with MUSC. With these settings (see Figure 39), a typical time-scale for the lifetime of the initial state modifications was 6 h-12 h. The three-dimensional model forcing is most likely a combination of the two types of forcing, however.

![Vertical specific humidity profile](image)

**Figure 40.** Specific humidity profiles from Karlstad April 28 2017 at 12 UTC. Clouds above the boundary layer were present at the time. In (a), the MUSC results are shown with cloud initialized forcing and a forcing time scale of 1 h, and (b) shows the results from the three-dimensional model. The dark blue lines are the initial profiles, and the light blue, green, yellow, red, and pink lines are forecasts with time steps of 1 h, 2 h, 3 h, 6 h, and 12 h.
Figure 41. Snow profiles from Karlstad April 28 2017 at 12 UTC. Clouds above the boundary layer were present at the time. In (a), the MUSC results are shown with cloud initialized forcing and a forcing time scale of 1 h, and (b) shows the results from the three-dimensional model. The dark blue lines are the initial profiles, and the light blue, green, yellow, red, and pink lines are forecasts with time steps of 1 h, 2 h, 3 h, 6 h, and 12 h.

5 Discussion

In this project, an evaluation of the method of using cloud initialization for improving short-range forecasts has been done. A cloud initialization technique similar to what was used by van der Veen (2012) was used to improve forecasts from HARMONIE-AROME using MESAN data. This technique involved using information on cloud fractions, cloud top heights, and cloud base heights from MESAN to modify moisture and hydrometeor concentrations as well as temperatures in each vertical column over each horizontal position in HARMONIE-AROME. Before applying this technique, an analysis of MESAN input data was done for quality checking purposes. Note, however, that no independent data, as in not used in MESAN, were available for this quality check. This means that no unbiased analysis of MESAN data is possible.

5.1 Evaluation of MESAN

Evaluation of three data sources in MESAN was conducted using subjective and statistical methods: the background model field, the satellite data, and the SYNOP station data. Time series of area-averaged cloud cover, maps of time-averaged cloud cover as well as correlations were used for this purpose. In the cloud cover time series as compared with both the background model and the SYNOP data (Figure 5a and Figure 12a), there appears to be a positive bias for the MESAN data. Figure 6 suggests that a large part of this positive bias comes from observations over sea, which is the satellite data. Also, the case study in Figure 16a shows
a time where there is a large difference between MESAN and the background model, and a lot of the differences are indeed over sea. This indicates that the satellite data contains more cloud cover than the background model field on average. The case study in Figure 19 shows that the satellite data may give good representation of small-scale cloud patterns, but perhaps too much cloud cover where clouds are present. This is backed up by Figure 24 where the fractional cloud category was removed, giving a cloud cover in better agreement with a satellite overview image. As seen in Figure 9 there is a definite positive bias with the satellite data compared to the MESAN data. With the SYNOP data, Häggmark et al. (1999) make the remark that automatic stations have height limitations that cause underestimations which were 3800 m during 1999, but are currently 7600 m. Still, this means that clouds with a cloud base of over 7600 m, such as most Cirrus clouds, are missed by the automatic stations. In Figure 14 most of the large differences between MESAN and SYNOP occur over Sweden and Finland. In Norway, the differences between MESAN and SYNOP are smaller. It is noteworthy that most of the SYNOP stations in Norway are manual, while most SYNOP stations in Sweden and Finland are automatic.

Correlations between all three input data sources and MESAN have been calculated and reasonably high values were, as expected, obtained. For MESAN the background model is the basis upon which cloud fraction data is obtained, before the observational data is added. Over land, a large weight is given to the SYNOP data, which is reflected in that the correlation coefficient in Figure 15 is especially high. This is good, as the SYNOP stations provide generally good quality data with a large temporal resolution, despite their limitations. For the satellite data in Figure 11 the situation is worse. Of course, over sea the satellite is of large importance for providing cloud observations. However, difficulties when determining cloud cover from satellite images seem to cause errors, which may be somewhat mended by the other sources for cloud data in MESAN, such as SYNOP over land or the background model field over sea. Such difficulties involve distinguishing between clouds and the underlying surface, and the interpretation of clouds (Häggmark et al., 1999). It seems that the functionality of the cloud initialization is currently limited by the quality of the satellite data. Although, one of the problems related to thin clouds has been identified. One should, however, keep in mind that the definition of a cloud does not take the concentrations of cloud water particles and ice particles into account. Therefore, it is not always easy to judge if a thin cloud exists or not (SMHI, 2013).

5.2 Evaluation of cloud initialization profiles

Section 4.2 of the results demonstrated the cloud initialization process on one-dimensional profiles of specific humidity, temperature, and hydrometeor concentration. Also, some experiments were done to evaluate certain aspects of the process as some aspects lacked documenta-
tion. Improvements used in the forecasts were also made.

MESAN was used to determine the height of the cloud base and cloud top, whereas clouds in HARMONIE-AROME were not previously added in the data assimilation cycles, and were instead formed through through balances in the physical fields in the model system. Thus, MESAN was used as a correction tool, dictating where clouds were actually present. Many previous studies involving cloud initialization made use of satellite-derived cloud products for this process, such as de Haan & van der Veen (2014) and Bayler, Aune & Raymond (1999). However, here the MESAN gridded analysis system combining multiple sources of observational data and a background model field allows for cloud products where weaknesses of using only satellite data are partly mended, and there will always be data available at all grid-points. This is suitable, as geostationary satellite data are less useful in the northern latitudes, and there is a variation in time when polar-orbiting satellite data are available.

Two primary purposes of the cloud initialization process were to modify the specific humidity profile according to where a cloud was present, and to remove hydrometeors above and below the cloud. As it was later found, the limit for which level of saturation clouds were formed (CCC) used in the earlier stages in the one-dimensional framework (Equation 12) did not produce very reliable results, but were useful in demonstrating the general effects of the cloud initialization. Figure 27 displays such a case, where the old $\text{CCC}$ was used during an example case. The effects are clear: inside the cloud, the specific humidity is set to the saturation specific humidity, and below and above the cloud, it is set to a fraction of the saturation specific humidity. Temperatures, as shown by Figure 28, are only slightly modified due to the iterations. Figure 29 also shows the removal of hydrometeors above the cloud. These modifications were made to ensure that a cloud is maintained in the model only at the level corresponding to MESAN clouds. Two possible points of critique are as follows: removing hydrometeors could cause underestimations in precipitation, and the specific humidity decrease below and above the cloud is quite abrupt. Firstly, no specific experiment on this hydrometeor removal effect on precipitation was made. However, later results such as Figure 37 and 41 showed how hydrometeors were formed within the first hour of forecast. This means that it does not appear take long for precipitation to be formed again if precipitation should be present, but further studies in this could be made. Secondly, the specific humidity change just below and just above the cloud is indeed large. In part, this could be useful for ensuring that the cloud does not turn out larger in the model than what is expected. Studies using a smoother transition between a cloud and no clouds for the specific humidity would be able to determine if this is the case.

The aspects of interest in this study were the multiple iterations of the cloud initialization process, how profiles would look using a more realistic $\text{CCC}$, and how using different saturation specific humidities would affect the results. Van der Veen (2012) made use of several iterations in order to take into account the mutual dependence of the temperature and the hu-
midity adjustments as the virtual temperature was meant to be conserved. This was done to
not initially affect the hydrostatic dynamics. In the HARMONIE-AROME version used in this
project, this was implemented together with a limit on specific humidity changes to not allow
for drastic deviations from the initial model state. However, Figure 30 and 31 demonstrate
some flaws in the implementation. The limit on specific humidity changes in Figure 30 are
such that drastic changes can occur given a sufficient number of iterations, and is therefore not
very useful in its current form. Also, Figure 31 showed how the differences between using one
and ten iterations were small. As such, a smaller number of iterations are most likely sufficient.
Van der Veen (2012) concluded that six iterations may be useful in the case of using satellite
cloud masks for cloud initialization in HIRLAM. From this study, however, it seems that even
only one iteration is sufficient when the limit check has been correctly implemented.

As for the CCC, Figure 32 shows the difference between the old CCC (red line) and the new
CCC (blue line) with new values for $RH_{\text{min}}$ and $RH_{\text{max}}$. Comparing Figure 33a and 33b, it is
seen that the humidity change below the cloud is not as abrupt with the new CCC, and is closer
to the original profile shown as the blue line in Figure 33a. This is not drastically different from
the radiosonde profile shown as the magenta line either. These profiles point at the new
CCC being more useful for the actual cloud initialization. Also, Figure 33a illustrated a weakness
in the cloud initialization process when handling several cloud layers. The radiosonde data
most likely suggests at least two different layers of clouds where this profile comes close to the
cloud initialized profile at the MESAN cloud base and at 500 hPa-600 hPa, whereas the cloud
initialized profile would show a cloud in the entire layer between the MESAN cloud base and
cloud top.

The sensitivity to using the saturation specific humidity with respect to water and with re-
spect to ice was examined in Figure 34. A temperature profile from a particular case was used
to calculate the saturation specific humidity with respect to ice and with respect to water. Figure
34 also contain $q_s \cdot CCC$, which is what the modified humidity profile would be above
and below a cloud. The conclusion from these results is that one should be careful not to use
the saturation specific humidity with respect to water at lower temperatures, as the modified
humidity might be high enough to cause the formation of high clouds during times when it is
undesired. This might particularly be a problem if high values of $RH_{\text{min}}$ and $RH_{\text{max}}$ are used.
Thus, using a weighted average between the two depending on the temperature seems reason-
able. Although, the exact temperatures for transition between the two that are appropriate could be studied further.

5.3 Forecast results

With the knowledge obtained in the previous sections, in section 4.3, MUSC is integrated
forward in time to see how the profiles change over time. This section examined how specific
humidity and hydrometeor concentrations changes over a 12 h time.

The first study involved producing an artificial cloud by adding clouds at different heights for two cases, which would simulate a low and a high cloud. This allowed for investigation of the sensitivity of using different forcing profiles and forcing time scales. The main conclusion was that there was a clear sensitivity to the forcing and to the forcing time scale. In the free atmosphere, the forcing was the most important aspect, but in the boundary layer, model physics also played an important role.

When looking at two similar cases, that is a case with a low cloud and a case with a high cloud, where the cloud is no longer artificial, additional interesting results were found. Comparing the MUSC results with the three-dimensional model results in Figure 39, 40 and 41 revealed that it seems appropriate to use a forcing from the original model profile with a forcing time scale of 3 h (such as with the dashed lines in Figure 36) to obtain MUSC results in good agreement with the three-dimensional model results. One weakness with using the original model profile as forcing profile, however, is how the hydrometeor formation may be hindered, as shown by the dashed lines in Figure 37b. Furthermore, it is clear that hydrometeors are formed very quickly when specific humidity is increased within the cloud, which supports the method of only modifying the specific humidity when adding a cloud. Modifications induced by the cloud initialization appear to remain for at least 6 h-12 h.

This also ties together with the results found in the parallel experiment in section 2.6, which served as a background for discussion. In those results, the standard deviations and biases showed that cloud initialization can have an effect of up to 12 h; the same as can be said for the MUSC results. The efficiency of cloud initialization also seemed to change depending on the location where it is utilized. Lower standard deviations were found over Norway than over Sweden. This could be due to the previously discussed varying quality of SYNOP measurements over these two countries, which has an effect on both the cloud initialization and the comparison that was done in Figure 3 as SYNOP station measurements were used for that comparison. Particularly Figure 14 displayed this. Biases over Norway fluctuated between 0 and 0.5 octa, while they were larger over most parts of Sweden and Denmark. As for the different parallel experiments in Figure 3, the CLD experiment showed lowest biases, but slightly higher standard deviations than the CRL and the MES experiments. In CLD, some actions were taken to not use clouds thinner than 1000 m. This was an attempt to, when the experiment started, take into account the misinterpretation of the fractional cloud category in the satellite product, which affected the MESAN clouds. This way of accounting for the cloud bias is probably sub-optimal and could lead to higher standard deviations, although the bias is reduced. Further experiments removing the fractional cloud class already at the stage when the MESAN product is produced would potentially lead to improved results.

All of the results point toward cloud initialization using MESAN data having an effect on
cloud forecasts in HARMONIE-AROME that lasts for approximately 12 h. Previous studies have come to the conclusion that using measurements to improve model cloud fields can have positive effects. White et al. (2017) used GOES-derived cloud fields to improve cloud fields in the Weather Research and Forecasting (WRF) model, and found an increase in agreement between GOES and WRF cloud fields of 14.02% for the domain of grid size 36 km and 4.96% for the domain of grid size 4 km. Van der Veen (2012) used EUMETSAT data for improving initial cloudiness data in HIRLAM, and found that a positive impact can be seen even after 24 h in 59% of the cases studied. Even in 1999, Bayler, Aune and Raymond (1999) concluded that using GOES sounder data for cloud fields in the Cooperative Institute for Meteorological Satellite Studies Regional Assimilation System gave improvements in the areal coverage of nonprecipitating clouds in the early periods of forecasts. To make the cloud initialization consistently better than the operational forecasts, a revised satellite cloud product should probably be used. Correcting the weaknesses found in the cloud initialization process may also contribute to better results in the future.

5.4 Recommendations

Recommendations regarding future cloud initialization work from the findings of this thesis are to: (1) use a MESAN product based on a revised interpretation of satellite clouds or possibly a cloud product based only on revised satellite data, and (2) to correct the weaknesses in the cloud initialization process pointed out here. Hopefully, this will result in improvements of cloud forecasts. One should also keep in mind the limitations of SYNOP cloud measurements when using them for verification of forecasts.

6 Conclusions

In this project, a cloud initialization method using MESAN cloud data was tested in MUSC, a one-dimensional vertical column version of HARMONIE-AROME, to improve cloudiness in the early hours of a forecast. Following is a list of conclusions that can be made from this investigation.

- MESAN overestimates cloud amounts as compared with satellite images. Smearing effects due to area-averaging in MESAN, in combination with the addition of satellite product data that also overestimate cloud amounts due to difficulties in interpretation, appear to be the cause.

- Some flaws in the cloud initialization method were found. A different critical relative humidity profile from the one used in the three-dimensional model was used for initial experiments in this project. However, this was changed to a profile that gave more reliable results.
Also, a limit on the specific humidity change was applied to avoid too large deviations from the model state. This was found to be applied within each iteration, but this meant that large changes could occur given a sufficient number of iterations. The limit check should either be removed or applied to the final result, and the number of iterations can be reduced.

- Alterations of the specific humidity and hydrometeor concentration profiles through cloud initialization can last over 12 h. Although, effects vary depending on the height a cloud is present in, as boundary layer effects can cause vertical mixing of profiles quicker than what usually happens in the free atmosphere.

- A reasonably good agreement between the MUSC results and the results from the three-dimensional HARMONIE-AROME was found. Differences depend mostly on the forcing and forcing time used in MUSC.

- Results from a parallel experiment showed how the cloud initialization can have an effect of up to 12 h, which was in agreement with the results in this project. These results varied depending on the area. Results found in this project shed some light on some aspects of this experiment. Such aspects were, for example, varying SYNOP measurement quality, and over-estimations of clouds in MESAN when no alterations to cloudiness were applied.

7 Acknowledgements

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8 References


Molod, A. (2012). Constraints on the Profiles of Total Water PDF in AGCMs from AIRS and a High-Resolution Model. *Journal of Climate*, vol. 25, pp. 8341 - 8352. DOI: 10.1175/JCLI-D-11-00412.1


Table 1. Atmospheric pressure and height of each corresponding vertical level model level. These values are for a standard atmospheric sea-level pressure of 1013.25 hPa.

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