Chapter 10
Operational Dust Prediction

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Abstract Over the last few years, numerical prediction of dust aerosol concentration has become prominent at several research and operational weather centres due to growing interest from diverse stakeholders, such as solar energy plant managers, health professionals, aviation and military authorities and policymakers. Dust prediction in numerical weather prediction-type models faces a number of

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challenges owing to the complexity of the system. At the centre of the problem is the vast range of scales required to fully account for all of the physical processes related to dust. Another limiting factor is the paucity of suitable dust observations available for model, evaluation and assimilation. This chapter discusses in detail numerical prediction of dust with examples from systems that are currently providing dust forecasts in near real-time or are part of international efforts to establish daily provision of dust forecasts based on multi-model ensembles. The various models are introduced and described along with an overview on the importance of dust prediction activities and a historical perspective. Assimilation and evaluation aspects in dust prediction are also discussed.

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10.1   Introduction

10.1.1   Motivation for Dust Forecasting

While the importance of airborne dust for visibility, air quality and climate has been recognised for a long time, it was only in the past decade that development of operational forecasting capabilities for atmospheric aerosols in general and dust in particular has intensified. Several reasons motivated the development of dust monitoring and forecasting capabilities:

1. Decision-makers have long desired the ability to forecast severe dust events in order to mitigate their impacts on transportation, military operations, energy and health. In some regions of the world, people's livelihoods are threatened by severe dust storms that can force the closing of roads and airports due to poor visibility. Health advisories to susceptible populations require dust information as input (Chap. 15). Commercial solar energy production systems require forecasts of solar insolation to help predict their contribution to the power grid, especially those that rely on direct solar radiation (Schroedter-Homscheidt et al. 2013). Dust also affects the semiconductor industry, which requires a clean atmosphere to manufacture electronic chips.

2. Dust interacts with atmospheric radiation and can significantly modify the Earth's radiative budget (Chap. 11). While the importance of dust–climate interactions has long been recognised (Chap. 13), it is only recently that the importance of dust for weather forecasting itself has been appreciated (Pérez et al. 2006a). Haywood et al. (2005) showed that the UK Met Office numerical weather prediction (NWP) model had a bias of -35 Wm^{-2} in its top-of-the-atmosphere radiative budget over the Saharan region because it neglected the effects of dust on radiation. Such systematic biases in NWP models can be addressed by prescribing better aerosol climatologies (e.g. Rodwell and Jung 2008), but interactive aerosols in NWP models are increasingly being exploited to improve the skill of weather forecasts.

3. Dust's infrared (IR) signature causes interference in satellite retrievals and subsequent assimilation of temperature, humidity and sea surface temperature (SST). For example, Weaver et al. (2003) show how TOVS (see Table 10.1 for a list of acronyms) temperature profiles can be contaminated by dust. Ruescas et al. (2011) demonstrated the impact on SST retrievals, which are used operationally as a boundary condition in models. Maddy et al. (2012) demonstrated significant dust impacts of up to 4 K on AIRS retrievals of the atmospheric temperature profile. Given the extreme loadings of some dust events from Africa and Asia, dust must be accounted for in models that utilise data assimilation based on IR wavelengths.

4. There is a pressing need to monitor the Earth's environment to better understand changes and adapt to them, especially in the context of climate. Since the dust cycle is closely related to meteorological conditions, the benefit of combining

Table 10.1 Acronyms of models, satellite sensors, organisations and networks

AD-Net	Asian Dust Network
AERONET	Aerosol Robotic Network
AIRS	Atmospheric Infrared Sounder
AMMA	African Monsoon Multidisciplinary Analysis
BSC-CNS	Barcelona Supercomputing Center-Centro Nacional de Supercomputación
CALIOP	Cloud-Aerosol Lidar with Orthogonal Polarization
CALIPSO	Cloud-Aerosol Lidar and Infrared Pathfinder Satellite Observations
CMA	China Meteorological Administration
CMAQ-KOSA	CMAQ coupled with dust deflation module
COAMPS	Coupled Ocean–Atmosphere Mesoscale Prediction System
CUACE/Dust	Chinese Unified Atmospheric Chemistry Environment for Dust
DREAM	Dust Regional Atmospheric Model
ECMWF	European Centre for Medium-Range Weather Forecasts
FNMOC	Fleet Numerical Meteorology and Oceanography Center
GCM	General Circulation Model
GEMS	Global Earth-system Monitoring using Space and in-situ data
GEOS-5	Goddard Earth Observing System Model, Version 5
GFS	Global Forecast System
GMAO	Global Modeling and Assimilation Office
GMES	Global Monitoring for Environment and Security (now Copernicus)
GOCART	Goddard Chemistry Aerosol Radiation and Transport
GSFC	Goddard Space Flight Center
IASI	Infrared Atmospheric Sounding Interferometer
ICAP	International Cooperative for Aerosol Prediction
IRI	International Research Institute for Climate and Society
JMA	Japan Meteorological Agency
LMD	Laboratoire de Météorologie Dynamique
LOA	Laboratoire d'Optique Atmosphérique
LSCE	Laboratoire des Sciences du Climat et l'Environnement
MACC	Monitoring Atmospheric Composition and Climate
MACC-II	Monitoring Atmospheric Composition and Climate- Interim Implementation
MASINGAR	Model of Aerosol Species in the Global Atmosphere
MEDUSE	MEditerranean DUSt Experiment
MISR	Multi-angle Imaging SpectroRadiometer
MODIS	Moderate Resolution Imaging Spectroradiometer
MRI	Meteorological Research Institute
MSG	Meteosat Second Generation
NAAPS	Navy Aerosol Analysis and Prediction System
NCEP	National Centers for Environmental Prediction
NEMS	NCEP Environmental Modeling System
NESDIS	National Environmental Satellite Data and Information Service
NGAC	NEMS GFS Aerosol Component
NMMB	Non-hydrostatic Multiscale Model
NMME	National Multi-Model Ensemble

(continued)

Table 10.1 (continued)

NOGAPS	Navy Operational Global Atmospheric Prediction System
NRL	Naval Research Laboratory
NTU	National Taiwan University
OMI	Ozone Monitoring Instrument
SEVIRI	Spinning Enhanced Visible and Infrared Imager
SEEVCCC	South East European Virtual Climate Change Center
TAQM	Taiwan Air Quality Model
TAQM-KOSA	TAQM coupled with dust deflation module
TEPA	Taiwan Environmental Protection Administration
TIROS	Television InfraRed Observation Satellite
TOMS	Total Ozone Mapping Spectrometer
TOVS	TIROS Operational Vertical Sounder
USGS	US Geological Survey
WMO	World Meteorological Organization
SDS-WAS	Sand and Dust Storm Warning Advisory and Assessment System
NA-ME-E	North Africa-Middle East-Europe
WRF	Weather Research and Forecasting
WRF-CHEM	Weather Research and Forecasting model coupled with Chemistry

the monitoring of the atmosphere with the monitoring of atmospheric species became clear very early in the planning of the Global Monitoring of the Environment and Security (GMES, now renamed Copernicus), which was the first European attempt at establishing an integrated analysis and forecasting system for atmospheric composition. As such, it was natural to extend the capability of NWP models to aerosol and chemical species (Hollingsworth et al. 2008).

10.1.2   A Brief History of Dust Forecasting

Westphal et al. (1987, 1988) is the first study to use a multidimensional, size-resolving, full physics numerical dust transport model, which demonstrated the practicality of numerical simulations of dust storms. In the following years, this concept was developed into capabilities for operational dust forecasting. Between 1991 and 1993, the predecessor version of the current DREAM dust model (Nickovic 1996; Nickovic and Dobricic 1996) was the first regional model in which dust concentration was built into the prognostic equations of the atmospheric model driver. This system was implemented at the Tunisian Meteorological Service and was run on an experimental daily basis in the period March–May 1995. Experimental daily dust forecasts were also performed during 1996–1997 within the EU-funded project "MEDUSE" when the model was driven by the atmospheric SKIRON system (Nickovic et al. 1997). The US Navy has invested in aerosol and dust forecasting since the mid-1990s through the development of the Navy Aerosol

Analysis and Prediction System (NAAPS) to address military needs. NAAPS was developed to include dust, smoke and sea salt, allowing predictions of aerosol concentrations, extinction and visibility starting from a prescribed meteorology. It began running in near real-time in 1999 and became the first fully operational aerosol model through transition to the Fleet Numerical Meteorology and Oceanography Center (FNMOC) in 2005, making 6-day forecasts twice daily. Since dust storms are a significant weather phenomenon in the Iraq region in winter and spring, Liu et al. (2007) modified the Coupled Ocean–Atmosphere Mesoscale Prediction System (COAMPS) to include a dust aerosol module fully integrated in the forecast model for use during Operation Iraqi Freedom in March and April 2003. Verification showed that COAMPS predicted the arrival and retreat of the major dust events and predicted the reduction in visibility (a measure of dust storm intensity) with an error of less than 1 km. These forecasts are still produced on an operational basis.

Operational forecasts have since become available from a number of NWP and research centres around the world (see Sect. 10.2). Many of these forecasts are now delivered through the regional nodes of the WMO Sand and Dust Storm Warning Advisory and Assessment System programme (WMO SDS-WAS; http://www.wmo.int/sdswas). Other forecasts are delivered through dedicated web interfaces to serve the purposes of the individual operational centres.

10.1.3 Specific Challenges in Dust Prediction

Numerical prediction of dust in NWP-type models faces a number of challenges. At the centre of the problem are the vast dimensions of scale required to fully account for all of the physical processes related to dust. Dust production is a function of surface wind stress and soil conditions (Chap. 5). Wind alone can range from synoptic-scale generation to mesoscale phenomena such as those produced by mountain passes or thunderstorms and micro-scale phenomena related to boundary-layer mixing (see Chap. 6). In addition to meteorology, one must consider the heterogeneity of the soil properties and emissions physics. Typically in global models, the functional form of the emission parameterisation is that of a power law in surface wind speed, making emissions highly sensitive to modelled wind fields. As a result, size-dependent emissions and transport are a major factor of uncertainty (Chap. 9). While the average size of dust particles which undergo long-range transport is surprisingly static (Dubovik et al. 2002; Maring et al. 2003; Reid et al. 2003, 2008), with a volume median diameter of $\sim$4–7 μm, short-lived giant mode particles (15–100 μm) are an important but largely unstudied component of dust that contributes to degraded air quality and IR radiative effects near source regions.

The sensitivity of dust emissions to scale has led to recognition of the importance of model resolution (Liu and Westphal 2001; Gläser et al. 2012; Takemi 2012). The quality of the modelled winds is dictated by characteristics such as horizontal resolution and numerical solver, and this quality is also limited by the relatively
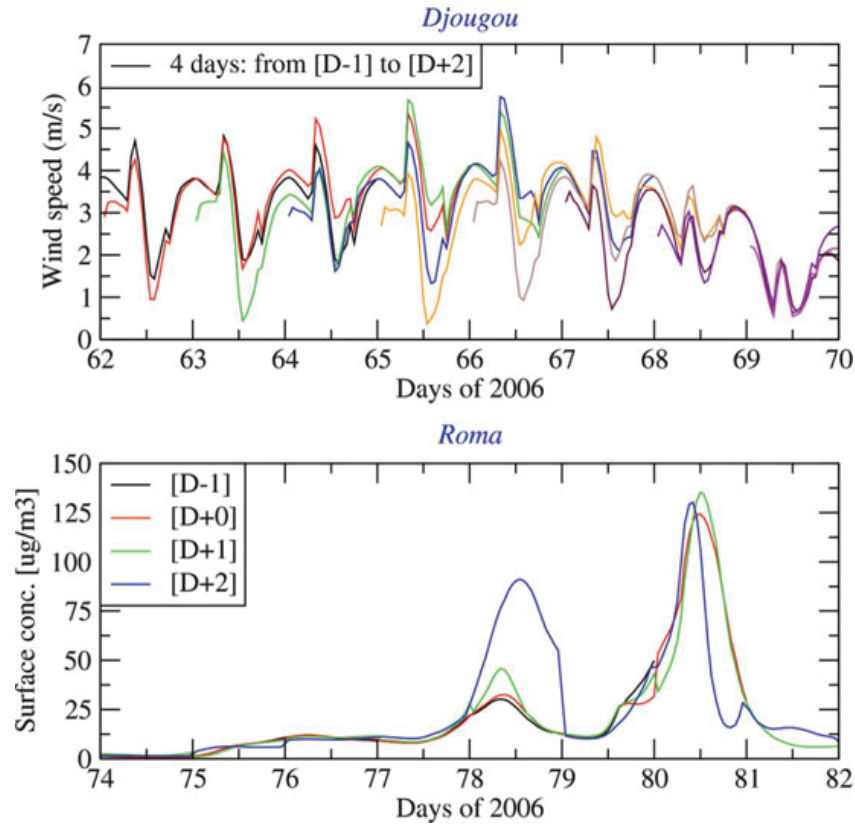
Fig. 10.1 Time series of modelled 10M winds in Djougou, 9.7 N, 1.6E (*top*), and corresponding dust surface concentrations in Rome, 41.9 N, 12.5E (*bottom*). Each coloured line represents successive forecasts of a single day starting 4 days in advance (*top*); and a forecast lead time (*bottom*), respectively

low amount of wind observations available to constrain the meteorological analysis driving the simulation. Moreover, nearly all large-scale models and regional models do not have the capability to resolve convective-scale phenomena (e.g. Reinfried et al. 2009) and are therefore missing potentially important emission sources (see Chap. 6 for more details). In the last few years, a good degree of accuracy in the prediction of dust at the synoptic scale and in some cases at the regional scale has been achieved, thanks to model improvements and in some cases data assimilation to the point that the information can be offered to forecasters as guidance.

The issue of predictability is illustrated with an example in Fig. 10.1, which presents time series of modelled 10 m wind speed and dust surface concentrations. For the wind speed, here presented for Djougou and modelled with WRF (Menut et al. 2009), each coloured line represents a forecast of 4 days. The corresponding days are superimposed and show the spread from one forecast to the following. The wind speed values range from 1 to 6 m/s, and the differences between each forecast do not exceed 1 m/s. This small variability is not important to those interested in the weather forecast. However, this variation becomes important when this wind speed is used to calculate dust emission and transport. The dust concentrations over Rome after long-range transport from Africa, modelled with CHIMERE, are presented in

the same figure. The variability in the dust surface concentrations at the various forecast ranges can be very large, especially compared to variations closer to the source at Djougou. Variations in dust can be of the same order of magnitude as the maximum concentrations of aerosols regulated by air quality policies.

Compounding predictability issues are challenges in dust observability. Both satellite- and ground-based observations are needed for nowcasting, data assimilation and evaluation tools. From satellite, a host of dust enhancement products is available to identify major dust features (see Chap. 7). However, many of these are qualitative in nature and as such cannot be readily used for assimilation in models. More quantitatively, aerosol optical depth (AOD) retrievals can be assimilated with corrections (e.g. Zhang and Reid 2006) but are commonly available only over water or dark surfaces. Over bright desert surfaces, where the aerosol signal cannot be so easily distinguished from the surface reflectance, "dark target" retrieval techniques (e.g. Kaufman et al. 1997) fail, and retrievals must exploit either different wavelengths like the Deep Blue algorithm (Hsu et al. 2004), multi-angle viewing such as with the MISR instrument (Martonchik et al. 2004) or polarimetric observations (e.g. Deuzé et al. 2001). But even in these circumstances, large errors exist, which can prohibit assimilation, and for the largest events, AODs are so high that the retrievals fail. This leaves models without reliable data for assimilation near source regions. Furthermore, while AOD is a common model benchmark, models carry mass, and there is virtually no reliable or representative data sets for mass evaluation in major dust source regions, where data is most needed. The little mass data that is available tends to come from short, episodic field missions. Lidar data of aerosol extinction and backscatter show promising potential towards constraining vertical profiles of aerosol fields and the height of the aerosol layers (Winker et al. 2007). Moreover, lidar depolarisation observations can be used to discriminate dust from other aerosol species.

The chapter is structured as follows. In Sect. 10.2, several operational and quasi-operational dust prediction models are described. Section 10.3 describes examples of regional and global multi-model ensembles for dust prediction that have been established in recent years to offer better information and products to the users. Key aspects of data assimilation for dust prediction are discussed in Sect. 10.4, while related technical details are given in Appendix A. Section 10.5 offers an overview of the type of verification and evaluation procedures these systems are subject to. Finally, Sect. 10.6 presents a summary and a future outlook on dust prediction activities.

10.2 Dust Prediction Models

This section summarises the characteristics of some of the current aerosol prediction models that are run in an operational or quasi-operational manner at various centres around the world. This compilation is not intended to be exhaustive. In an effort to be as inclusive as possible, both global and regional systems are described.

Further information regarding the model characteristics such as horizontal and vertical resolution and dust emission and deposition parameterisations is provided in Tables 10.2 and 10.3 together with references for each model.

10.2.1   Global Models

ECMWF/MACC Aerosol Prediction System

Starting in 2008, ECMWF has been providing daily aerosol forecasts including dust as part of the EU-funded projects GEMS, MACC and MACC-II (see Table 10.1 for acronyms). All data are publicly available online at http://www.copernicus-atmosphere.eu. A detailed description of the ECMWF forecast and analysis model including aerosol processes is given in Morcrette et al. (2009) and Benedetti et al. (2009). The initial package of ECMWF physical parameterisations dedicated to aerosol processes mainly follows the aerosol treatment in the LOA/LMD-Z model (Boucher et al. 2002; Reddy et al. 2005). Five types of tropospheric aerosols are considered: sea salt, dust, organic and black carbon and sulphate aerosols. Prognostic aerosols of natural origin, such as mineral dust, are described using three size bins. Emissions of dust depend on the 10 m wind, the soil moisture, the UV-visible component of the surface albedo and the fraction of land covered by vegetation when the surface is snow-free. A correction to the 10 m wind to account for gustiness is also included (Morcrette et al. 2008). MODIS AOD data are routinely assimilated in a 4D-Var framework. The global modelling system of MACC-II is also used to provide the boundary conditions for an ensemble of more detailed regional air quality models that are used to zoom in on the European domain and produce 4-day forecasts of air quality.

FNMOC Navy Aerosol Analysis and Prediction System

Based on the Danish Eulerian Hemispheric Model (Christensen 1997; Westphal et al. 2009), NAAPS is an offline chemical transport model currently running with single-size bin dust, smoke, sulphate and sea salt at $1/3 \times 1/3°$ and 30 levels driven by the 0.5° Navy Operational Global Atmospheric Prediction System (NOGAPS; Hogan and Rosmond 1991). Operational NAAPS has MODIS data assimilation via a 2D-Var framework (Zhang et al. 2008), with 3D-Var and ensemble Kalman filter (EnKF) systems in development (e.g. Zhang et al. 2011). Next generation models, such as an ensemble version of NAAPS run from the ensemble NOGAPS forecast, are run quasi-operationally NRL at 1° resolution. Dust emission in NAAPS is based on modelled friction velocity to the fourth power coupled to a source map which was empirically derived from TOMS Aerosol Index products. A transition is in place to adopt the recently expanded 1 km high-resolution database of Walker et al. (2009). Data products with verification tools can be found at http://www.nrlmry.navy.mil/aerosol/ with data archives at http://www.usgodae.org/.

Table 10.2 Global model synopsis

Model	GEOS-5	MACC-II	MASINGAR	MetUM	NAAPS	NGAC	NMMB/BSC-Dust
Institution	NASA	ECMWF	JMA/MRI	UK Met Office	FNMOC/NRL	NCEP	BSC-CNS
Meteorological driver	GEOS-5	IFS	MRI/JMA98 AGCM	MetUM	NOGAPS	NEMS GFS	NMMB/NCEP
Source mask	Ginoux et al. (2001)	Morcrette et al. (2009)		HWSD, FAO (2009)	USGS, TOMS-AI, Walker et al. (2009)	Ginoux et al. (2001)	USGS-FAO with Ginoux et al. (2001) and NESDIS vegetation fraction climatology (Ignatov and Gutman 1998)
Emission scheme	Based on Ginoux et al (2001)	Uplifting (Ginoux et al. 2001; Morcrette et al. 2008, 2009)	Uplifting with threshold wind velocity = 6.5 m/s (Gillette 1978; Tegen and Fung 1994)	Gillette (1978), Marticorena and Bergametti (1995), Woodward (2001, 2011)	Westphal et al. (1988)	Dust uplifting following Ginoux et al (2001)	Saltation and sandblasting (White 1979; Marticorena and Bergametti 1995; Marticorena et al. 1997; Janjic 1994; Nickovic et al. 2001)
Deposition schemes	Colarco et al. (2010)	Wet/dry deposition, in-cloud and below-cloud scavenging (Morcrette et al. 2009)	Tanaka et al. (2003)	Wet/Dry deposition (Woodward 2001)	Walcek et al. (1986), Iversen (1989)	Colarco et al. (2010)	Dry deposition (Zhang et al. 2001) and wet deposition (Ferrier et al. 2002; Betts 1986; Janjic, 1994)
Sedimentation scheme	Colarco et al. (2010)	Morcrette et al. (2009)	Tanaka et al. (2003)	Woodward (2001)	Hinds (1982)	Colarco et al. (2010)	Zhang et al. (2001)
Horizontal resolution	0.25° × 0.3125°	0.8° × 0.8°	1.125° × 1.125°	0.3516° × 0.2344°	1/3° operational 1° research	T126 (~1°)	1.40625° × 1.0°

Vertical resolution	72 sigma-pressure hybrid layers. Top: 0.01 hPa	60 σ-layers	20 σ-p hybrid layers	70 levels. Charney–Phillips grid	25 layers	64 sigma-pressure hybrid layers, top at 0.2 hPa	24 σ-hybrid layers
Height first layer		10 m (above the surface)	40 m	20 m	20 m	20 m	60 m (above surface)
Radiation interactions	Direct effects fully included	Yes (not activated)	No	Yes (not activated)	No	Yes (not activated)	Yes (not activated)
Transport size bins	5 bins centred at 0.73 μm, 1.4 μm, 2.4 μm, 4.5 μm, and 8.0 μm	3 bins (0.03–0.55 μm, 0.55–0.9 μm and 0.9–20 μm)	10 bins (0.1–10 μm)	2 (0.1–2 μm and 2–10 μm)	1	5 bins centred at 0.73 μm, 1.4 μm, 2.4 μm, 4.5 μm, and 8.0 μm	8 bins (0.1–10 μm) Tegen and Lacis (1996)
Data assimilation	Yes	Yes AOD550/ MODIS	No	Yes AOD550/ MODIS	MODIS AOD (Zhang and Reid 2006; Zhang et al. 2008)	No	No

Table 10.3 Regional models synopsis

Model	BSC-DREAM8b	CHIMERE	CMAQ-KOSA	COAMPS	CUACE/Dust	DREAM8-NMME-MACC	NMMB/BSC-Dust	TAQM-KOSA
Institution	BSC-CNS	LMD	NTU/TEPA	FNMOC/NRL	CMA/CAMS	SEEVCCC	BSC-CNS	NTU/TEPA
Meteorological driver	Eta/NCEP	WRF	MM5/WRF	COAMPS	MM5 and GRAPES	NMME/NCEP	NMMB/NCEP	MM5/WRF
Meteorological initial fields	NCEP/GFS	NCEP/GFS	NCEP/GFS	COAMPS		ECMWF	NCEP/GFS	NCEP/GFS
Source mask	USGS-FAO with Ginoux et al. (2001)		Wang et al. (2000) + MODIS land type	Walker et al. (2009)	Gong et al. (2003a, b), Zhang et al. (2003)	USGS-FAO with Ginoux et al. (2001)	USGS-FAO with Ginoux et al. (2001) and NESDIS	Wang et al. (2000)
Emission scheme	Uplifting (Shao et al. 1993; Janjic 1994; Nickovic et al. 2001)	Saltation and sandblasting (Marticorena and Bergametti 1995; Alfaro and Gomes 2001; Menut et al. 2005)	Uplifting (Wang et al. 2000)	Lifting (Liu and Westphal 2001)	Marticorena and Bergametti (1995), Alfaro et al. (1997), Alfaro and Gomes (2001)	Uplifting (Shao et al. 1993; Janjic 1994; Nickovic et al. 2001)	Saltation and sandblasting (White 1979; Marticorena and Bergametti 1995; Janjic 1994; Nickovic et al. 2001)	Uplifting (Wang et al. 2000)
Deposition schemes	Dry deposition (Zhang et al. 2001) and below-cloud scavenging (Nickovic et al. 2001)	Dry deposition (Venkatram and Pleim, 1999) and wet deposition	Dry deposition and below-cloud scavenging (CMAQ; Byun and Schere 2006)	Dry and wet deposition and below-cloud scavenging (Liu et al. 2001)		Dry deposition (Zhang et al. 2001) and below-cloud scavenging (Nickovic et al. 2001).	Dry deposition (Zhang et al. 2001) and wet deposition (Ferrier et al. 2002; Betts 1986; Janjic 1994)	Dry deposition and below-cloud scavenging (RADM2; Stockwell et al. 1990)

Sedimentation scheme	Gravitational settling (Zhang et al. 2001)	Gravitational settling (Zhang et al. 2001)	Gravitational settling (CMAQ; Byun and Schere 2006)	Gravitational settling	Gravitational settling (Zhang et al. 2001)	Gravitational settling (Zhang et al. 2001)	Gravitational settling (RADM2; Stockwell et al. 1990)
Horizontal resolution	$1/3° \times 1/3°$	Variable ($1° \times 1°$ for dust)	81 and 57 km	1–81 km	$0.25° \times 0.25°$	$1/3° \times 1/3°$	81 and 57 km (3 km for local dust)
Vertical resolution	24 Eta-layers	30 σ-layers	15 σ-layers	48 layers	24 σ-hybrid layers	40 σ-hybrid layers	15/19 σ-layers
Height first layer	86 m (above sea level)	40 m (above the surface)	40 m (above the surface)	20 m	86 m (above sea level)	100 m (above surface)	40 m (above surface)
Radiation interactions	Yes	No	No	No	No	Yes (not activated)	No
Transport size bins	8 bins (0.1–10 μm); Tegen and Lacis (1996)	9 bins (0.039–20 μm)	1–10 bins (0.04–36 μm); Tegen and Lacis (1996)	12 bins (0.005–20.48 μm); Tegen and Lacis (1996)	8 bins (0.1–10 μm)	8 bins (0.1–10 μm)	12 bins (0.1–24.6 μm)
Data assimilation	No	No	No	Yes	Yes, using the MODIS-MACC initial fields	No	No

JMA Operational Dust Forecast Model

The Japan Meteorological Agency (JMA) has been providing the "Aeolian Dust Information" to the general public via its website (http://www.jma.go.jp/en/kosa/) since January 2004. The operational numerical dust forecast in JMA is based on the Model of Aerosol Species in the Global Atmosphere (MASINGAR) (Tanaka et al. 2003), which is coupled with the MRI/JMA98 AGCM. Dust particles are logarithmically divided into 10 discrete size bins from 0.1 to 10 μm in radius. The operational version of MASINGAR calculates the emission flux of dust as a function of the third power of 10 m wind velocity, soil moisture, soil type, snow cover and vegetation cover. Snow cover by JMA surface analysis and monthly mean MODIS-retrieved leaf area index are used to constrain the erodible surface. JMA is planning to update the operational dust forecast model to be based on the latest global climate model MRI-CGCM3 (Yukimoto et al. 2012).

Met Office Dust Prediction System

The publicly available dust forecasts from the UK Met Office are produced by the global NWP configuration of the Met Office Unified Model (MetUM^{TM}). The dust scheme is essentially that of Woodward (2001) with modifications as described in Woodward (2011) and Collins et al. (2011). The dust emission scheme is represents an initial horizontal/saltation flux in a number of size bins with a subsequent vertical flux of bare soil particles from the surface into the atmosphere. The global NWP model uses only two of the original nine size bins. The magnitude of the emission is a cubic function of the exceedance of the friction velocity over bare soil with respect to a threshold value, determined from the model wind field and boundary-layer structure. The horizontal flux is converted to the vertical flux by first limiting it using the clay fraction in the soil texture data set and then partitioning into the new bins with a prescribed emitted size distribution. Johnson et al. (2011) gives an in-depth description and evaluation of the Met Office dust forecasts in a limited area model over North Africa.

NASA GEOS-5 Aerosol Forecasting System

The Goddard Earth Observing System (GEOS-5; Rienecker et al. 2008) is an Earth system model maintained at the NASA Global Modeling and Assimilation Office (GMAO) to support NASA missions and climate studies. Aerosols are carried online and radiatively coupled to the GEOS-5 AGCM using a version of the Goddard Chemistry Aerosol Radiation and Transport module (GOCART, Chin et al. 2002). GOCART treats the sources, sinks, transport and optical properties of dust, sea salt, black and organic carbon and sulphate. For dust, GOCART employs a

topographic source function and uses a wind speed threshold for dust emissions. The dust particle-size distribution is discretised into five bins. Further description of the aerosol module, its implementation in the GEOS modelling system and its performance is provided in Colarco et al. (2010). The current version of the GEOS-5 forecasting system performs twice daily 5-day forecasts at $0.25° \times 0.3125°$ latitude/longitude horizontal resolution in a quasi-operational framework. AOD based on MODIS observations are assimilated in a 3D-Var framework.

NCEP/NGAC Global Aerosol Forecasting System

Since September 2012, NOAA NCEP has provided 5-day global dust forecasts once per day (at 00 UTC cycle) from the NEMS GFS Aerosol Component (NGAC) system. The forecast model is the Global Forecast System (GFS) within the NOAA Environmental Modeling System (NEMS), and the aerosol component is GOCART. The development of NGAC is part of NCEP's modelling efforts towards a unified modelling framework. The GOCART parameterisations, developed and implemented within GMAO's GEOS-5 Earth system model (Colarco et al. 2010), were coupled with NCEP's NEMS GFS to establish the first interactive atmospheric aerosol forecasting system at NCEP (Lu et al. 2010, 2013). While the ultimate goal at NCEP is a complete Earth system model with the inclusion of aerosol-radiation feedback and aerosol–cloud interaction, the current operational configuration is to maintain a low-resolution forecast-only system for aerosol prediction and a high-resolution forecasting and analysis system for medium-range NWP.

NMMB/BSC-Dust Model

The NMMB/BSC-Dust model (Pérez et al. 2011) is the global and regional dust forecast operational system developed and maintained at the Barcelona Super-computing Center–Centro Nacional de Supercomputación (BSC-CNS). It is an online multi-scale atmospheric dust model designed and developed at BSC-CNS in collaboration with NOAA NCEP, NASA Goddard Institute for Space Studies and the International Research Institute for Climate and Society (IRI). The dust model is fully embedded into the Non-hydrostatic Multiscale Model (NMMB) developed at NCEP (Janjic et al. 2011 and references therein) and is intended to provide short- to medium-range dust forecasts for both regional and global domains. The NMMB/BSC-Dust model includes a physically based dust emission scheme, which explicitly takes into account saltation and sandblasting processes. It includes an 8-bin size distribution and radiative interactions. The NMMB/BSC-Dust model has been evaluated at regional and global scales (Pérez et al. 2011; Haustein et al. 2012). These developments represent the first step towards a unified multiscale chemical-weather prediction system at BSC-CNS (NMMB/BSC-CTM; Jorba et al. 2012).

10.2.2 Regional Models

CHIMERE Model

The CHIMERE model is dedicated to the transport and chemistry of numerous gaseous and aerosols species. It has been in development for more than 15 years and is intended to be a modular framework available for community use. The dust emission fluxes take into account physical processes such as saltation and sandblasting. A complete description of the dust calculation is presented in Menut et al. (2007). For long-range transport simulations, the model domain includes Africa and Europe requiring a coarse horizontal grid spacing of $1 \times 1°$. In order to take into account the subgrid-scale variability of winds, dust emissions are estimated using a Weibull distribution for the wind speed (Menut 2008). In Menut et al. (2009), an intensive observation period of the African Monsoon Multidisciplinary Analysis (AMMA) programme was modelled in forecast mode to study the variability of modelled surface dust concentrations. It was shown that most of this variability comes from model uncertainties in emissions, transport and deposition as well as from variations in the meteorological fields (see Fig. 10.1).

CUACE/Dust

CUACE/Dust is an integrated atmospheric chemistry modelling system applied for dust (see special issue at http://www.atmos-chem-phys.net/special_issue81.html), which has been operationally run for dust forecasts in China Meteorological Administration (CMA) since 2004 and for the WMO SDS-WAS Asia Node-Regional Centre since 2007. CUACE has been designed as a unified chemistry module to be easily coupled with atmospheric models through a common interface. Its aerosol module utilises a size-segregated multi-component algorithm for different types of aerosols including dust, sea salt, black and organic carbon, nitrate and sulphate (Gong et al. 2003a; Zhou et al. 2008, 2012). A detailed desert distribution with soil texture data base and dust particle-size distributions measurements from nine major deserts for China was adopted (Gong et al. 2003b; Zhang et al. 2003). One of the unique features of the CUACE/Dust is the implementation of a 3D-Var data assimilation system using both satellite and surface observations in near real-time to improve the initial conditions and hence the forecast results (Niu et al. 2008). A scoring system has been developed where observations from various sources concerning dust aerosol, i.e. surface observations of sand and dust storms and satellite retrieved Infrared Difference Dust Index (IDDI; Hu et al. 2008), are integrated into a geographic information system (Wang et al. 2008).

The DREAM/BSC-DREAM8b Models

The Dust Regional Atmospheric Model (DREAM; Nickovic et al. 2001) is based on the Euler-type partial differential nonlinear equation for dust mass continuity and is driven by NCEP/Eta. The model was developed at the Euro-Mediterranean Centre of Insular Coastal Dynamics (ICoD). In May 2005, the operational version of DREAM was transferred to the Environmental Modelling Laboratory of the Technical University of Catalonia (UPC) and in September 2006 to the BSC-CNS. A set of updates during 2002–2005 (Nickovic 2002, 2003, 2005; Nickovic et al. 2004) included a source function based on the 1 km USGS land use data, eight particle-size bins and an initial version of the dust-radiation feedback scheme in cooperation with the Oceanographic Institute (Erdemli, Turkey). In addition to these developments, the updated BSC-DREAM8b v2 model (Pérez et al. 2006a, b; Basart et al. 2012a) includes an improved source mask and updated wet and dry deposition scheme. The BSC-DREAM8b v2 model provides daily dust forecasts at BSC-CNS website (http://www.bsc.es/projects/earthscience/BSC-DREAM/) which are evaluated in near real-time against satellite- and ground-based observations. The model has been extensively evaluated against observations (see, e.g. Basart et al. 2012b).

Since recently, DREAM8-NMME-MACC, which is driven by the NCEP/NMME non-hydrostatic model and includes assimilation of MODIS AOD (Pejanovic et al. 2010; Nickovic et al. 2012), provides daily dust forecasts available at the South East European Virtual Climate Change Center (SEEVCCC; http://www.seevccc.rs/).

FNMOC Coupled Ocean–Atmosphere Mesoscale Prediction System (COAMPS)

NRL has developed an online, multi-bin dust module inside COAMPS, simulating the evolution of the spatial and size distributions of mineral dust particles and passive volcanic ash. Beginning with operational transition to FNMOC in 2001 for Operation Iraqi Freedom (Liu and Westphal 2001; Liu et al. 2007), COAMPS dust simulations are now run on multiple domains over the world daily, with forecasts out to 3 days at resolutions of up to 1 km. The aerosol physical processes of sedimentation, dry deposition and wet removal are calculated using the dynamics and cloud fields of COAMPS. The dust source is based on the 1 km high-resolution dust source database of Walker et al. (2009) that has been developed based on empirical relationships between satellite observed dust and static land cover information.

Regional Mineral Dust Forecast Model in Taiwan

Taiwan's Environment Protection Administration (TEPA) has conducted East Asian dust storm forecasts since 2002 in collaboration with the Department of Atmospheric Sciences, National Taiwan University (NTU). They incorporated the dust deflation module of Wang et al. (2000) into the Taiwan Air Quality Model (TAQM) in 2002 and into the CMAQ model in 2010. Some of the model details can be found in Chen et al. (2004) and Table 10.3. The dust-coupled TAQM (or TAQM-KOSA) is run twice a day for 57 and 81 km horizontal grid spacing, each providing a 5-day forecast. TAQM-KOSA has also been used as a research tool to study dust effects on cloud microphysics and marine phytoplankton bloom by the NTU group. Studies of dust produced from dry riverbeds and agricultural lands using 3 km grid spacing showed that these local sources may raise regional PM concentration more than dust from long-range transport. Local daily dust forecasts have been included in routine operation since 2010. The dust scheme is being improved and incorporated into WRF and WRF-CHEM models and coupled with the cloud microphysical scheme to provide better calculation of in-cloud and below-cloud scavenging of dust as well as dust-radiation feedback. These versions will be gradually incorporated into daily operation after extensive tests.

## 10.3   Multi-model Ensembles

Ensemble prediction aims to describe the future state of the atmosphere from a probabilistic point of view. Multiple simulations are run to account for the uncertainty of the initial state and/or for the inaccuracy of the model and the mathematical methods used to solve its equations. Multi-model forecasting intends to alleviate the shortcomings of individual models while offering an insight on the uncertainties associated with a single-model forecast. Use of ensemble forecast is especially encouraged in situation associated to unstable weather patterns or in extreme conditions. Ensemble approaches are also known to have more skills at longer ranges (>6 days) where the probabilistic approach provides more reliable information than a single model run due to the model error increasing over time. Moreover, an exhaustive comparison of different models with each other and against multi-model products as well as observations can reveal weaknesses of individual models and provide an assessment of model uncertainties in simulating the dust cycle. Multi-model ensembles also represent a paradigm shift in which offering the best product to the users as a collective scientific community becomes more important than competing for achieving the best forecast as individual centres. This new paradigm fosters collaboration and interaction and ultimately results in improvements in the individual models and in better final products. Two examples of multi-model ensembles for dust prediction are shown below.

10.3.1 The International Cooperative for Aerosol Prediction (ICAP) Multi-model Ensemble

As a result of the maturity of an international community of global aerosol forecast model developers (Reid et al. 2011; Benedetti et al. 2011), the creation of broadly acceptable norms, benchmarks and scorecards to evaluate aerosol forecast skill has become an important issue. At the same time, the NWP community has recognised the value in multi-model ensembles in developing probabilistic forecast tools. Similarly, ensembles of global aerosol analyses are becoming an important tool for climate studies (Huneeus et al. 2011). In response to community needs and views, member developers of the International Cooperative for Aerosol Prediction (ICAP) created a developmental global multi-model ensemble (MME) (Sessions et al. 2014) to allow exploration of relative differences between models and devise tools for probabilistic prediction. Current models in the ICAP-MME dust component include (1) NMMB/BSC-CTM, (2) ECMWF MACC, (3) JMA MASINGAR, (4) NASA GEOS-5, (5) NOAA NGAC, (6) NRL developmental NAAPS and (7) NRL 20-member ensemble mean E-NAAPS (see Sect. 10.2.1). To allow for the inclusion of quasi-operational models, the ICAP-MME is run 24 h behind actual time, which reduces the forecast range from 5 to 4 days. Daily products include a host of maps, mean-spread plots, verification plots and threat scores. As an example of available products, Fig. 10.2 shows the 24 h dust forecasts of aerosol optical depth at 550 nm wavelength valid for 2 January 2013, from the participating models. The maps of AOD show a high degree of consistency of the dust forecasts among the various models. However, there are differences in the magnitude of the AOD field and also in some features, such as the plume being transported towards the North Atlantic which is not present in all models. While currently ICAP-MME data is only available to participating member centres, it is expected to be made public on a quasi-operational basis by the end of 2014.

10.3.2 WMO SDS Regional Dust Prediction Multi-model Ensemble

The Sand and Dust Storm Warning Advisory and Assessment System (SDS-WAS) is a programme of the World Meteorological Organization (WMO) with the mission to enhance the ability of countries to produce and deliver to end users timely and precise sand and dust storm forecasts (Terradellas et al. 2011). The WMO SDS-WAS Regional Centre for Northern Africa, Middle East and Europe (NA-ME-E) coordinates the exchange of forecast products generated by different dust models (BSC-DREAM8b v2, MACC, DREAM8-NMME-MACC, CHIMERE, NMMB/BSC-Dust, MetUM, GEOS-5 and NGAC) and conducts a model inter-comparison and evaluation within its geographic scope (Terradellas et al. 2012). Two products describing centrality (multi-model median and mean) and two
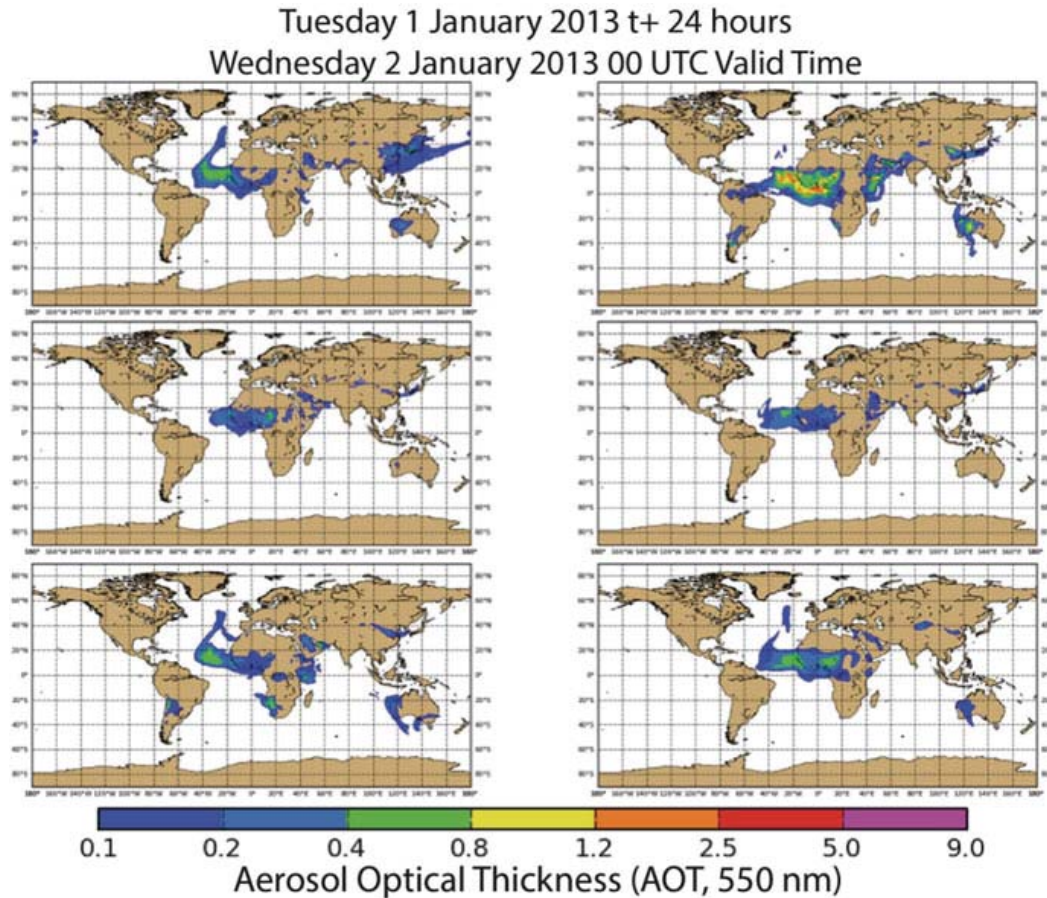
Fig. 10.2 Example of ICAP-MME 24 h dust forecasts of aerosol optical depth at 550 nm wavelength valid for 2 January 2013. Models are ordered as follows: NAAPS (*top left*), GEOS-5 (*middle left*), MASINGAR (*bottom left*), NMMB/BSC-CTM (*top right*), MACC/ECMWF (*middle right*) and NCEP NGAC (*bottom right*)

products describing spread (standard deviation and range of variation) are calculated and are available daily at http://sds-was.aemet.es/. An example of products is shown in Fig. 10.3. In order to generate them, the model outputs are bilinearly interpolated to a common grid mesh of $0.5° \times 0.5°$. The daily SDS-WAS NA-ME-E multi-model median (together with the individual models) is continuously evaluated against data from the Aerosol Robotic Network (AERONET; see also Chap. 7).

10.4 Data Assimilation for Dust Prediction

10.4.1 Introduction

Data assimilation offers a mathematical framework to incorporate observational information into models. When dust prediction was started at various operational
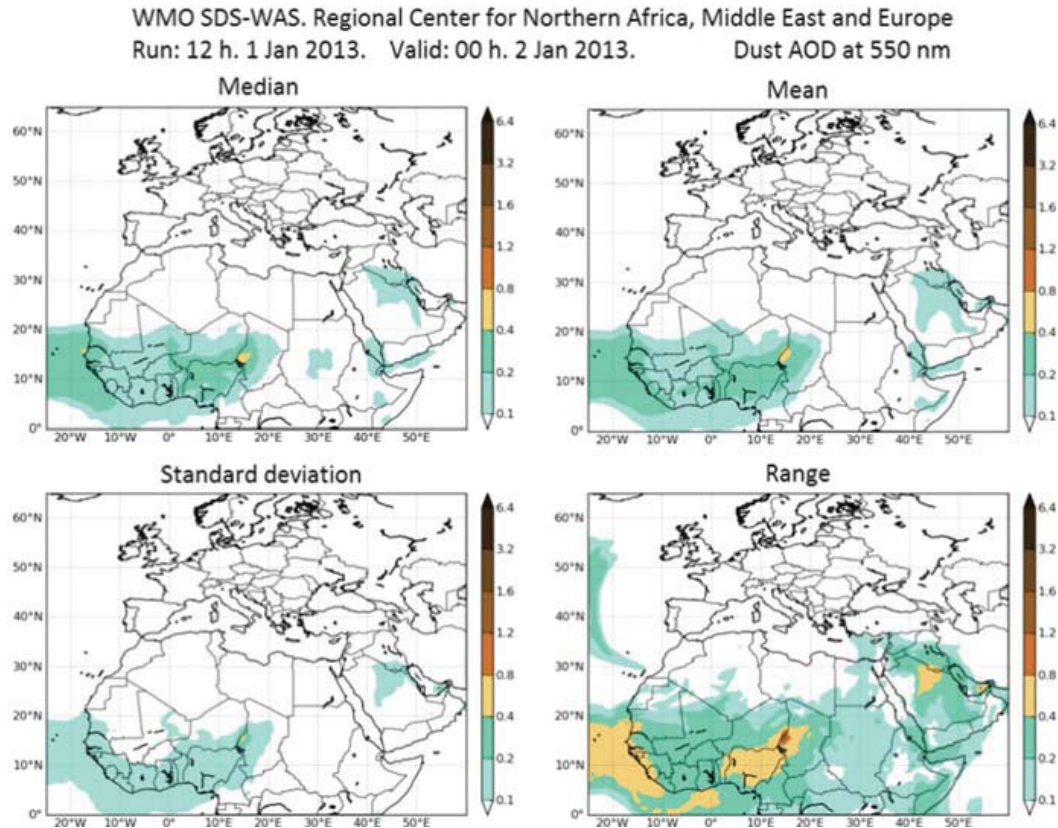
Fig. 10.3 Example of multi-model products issued by the WMO SDS-WAS Regional Center NA-ME-E: dust optical depth at 550 nm wavelength forecast for 2 January 2013. The *top two panels* describe centrality (multi-model median and mean), and the *bottom two panels* describe spread (standard deviation and range of variation)

centres with multi-annual experience in assimilation, it was a natural development to extend the system to include observations relevant to dust, and aerosols in general, in an effort to initialise the model also for these additional variables. Nowadays, most operational centres with aerosol forecasting capabilities run systems which include an aerosol analysis. While the general assimilation tools can be ported in a straightforward manner to any variable, there are some specific challenges in dust/aerosol assimilation which are mainly related to the paucity of suitable dust observations available for assimilation and the complexity of extracting specific dust signals from satellite radiances which are affected by all aerosol species and other atmospheric quantities. Moreover, due to the complex radiative transfer calculations needed to model aerosol-affected radiances from the visible channels of the current generation of imagers (see Chap. 12), most centres assimilate retrieved products (e.g. aerosol optical depth, AOD) rather than the raw observations. Even this approach has its limitations as AOD observations from sensors with visible channels are not available over bright surfaces such as deserts. This is, for example, the case for the standard AOD data from the MODIS sensor on board of the NASA Terra and Aqua satellites (see Chap. 7), which represent the most important source of near real-time information for the systems with assimilation capabilities.

MODIS data are assimilated in the ECMWF, NRL and NASA forecasting system, although each centre adopts individual strategies for filtering and bias correcting the MODIS observations. As mentioned, the standard MODIS product provides no information on dust over the sources, but it does, for example, over the Atlantic Ocean where dust outflow from the Sahara is the main contributor to the aerosol load. In regions that are not observed, therefore, the model plays a large role in generating that information. Recently, enhanced efforts have been made at several centres to include other observations, for example, the land AOD product from the SEVIRI instrument on board of the MSG payload at the UK Met Office, MODIS Deep Blue at NRL, OMI data at NASA and lidar backscatter at ECMWF, NRL and JMA. JMA/MRI has been pioneering the possibility of assimilating lidar data, with proven benefits on the dust prediction with their offline assimilation and forecasting system (Sekiyama et al. 2010, 2011). In what follows, the main concepts of data assimilation are briefly discussed with focus on some specific aspects related to dust/aerosol assimilation. Technical details are provided in Appendix A.

10.4.2 Main Concepts

Data assimilation is the process of finding the most likely estimation of the true system state via the combination of observations and any available a priori information. In the particular case of forecasts, this a priori information corresponds to the output of model simulations. In other words, data assimilation is an objective way of filling in information gaps and finding the optimal estimate of the true state by minimising the variance of the a posteriori probability distribution function describing the state. This approximation of the true state is the *analysis*. The method most commonly used to obtain an analysis is the least-squares method, which is based on minimising the variance of the a posteriori distribution according to a weighted-mean calculation. One of the simplest forms of analysis is, for example, the interpolation of the differences between model and observations from the locations where the observations have been taken back to the model grid points in order to correct the prior model state (*first guess*). Usually, the weights assigned are inversely proportional to the errors in the observations and the errors in the model first guess. No matter how complicated the schemes and systems involved are, the basic concepts of data assimilation can always be illustrated by this weighted-mean calculation.

Most of the current dust prediction systems rely on assimilation developments already in place for the meteorological models: for example, ECMWF uses the incremental 4D-Var formulation with augmented control vector to include an aerosol total mixing ratio variable (Benedetti et al. 2009). At the Met Office, 4D-Var assimilation of dust observations follows a similar approach, using total dust concentration as the analysis variable to be optimised (control variable). NRL and NASA GMAO use 2D- and 3D-Var approaches. In the case of the regional NMME-DREAM8 dust model (Pejanovic et al. 2010), an assimilation method based on Newtonian relaxation is applied using background dust concentrations from the DREAM dust model and the ECMWF dust analysis.

It is important to remember that most of these aerosol analysis systems solve an initial condition problem: the analysis is used to obtain the initial conditions in the aerosol fields, so that the subsequent forecast matches the observations. In some cases, finding the optimal initial conditions for the atmospheric aerosol concentrations is not sufficient as the actual aerosol amounts may be due to sources that are not accounted for. Studies which include direct estimation of emissions have been promising both for dust (Sekiyama et al. 2011) and other aerosol types (Huneeus et al. 2012), and it is likely that future aerosol analysis systems will include emission parameters in their control variables.

The other aspect which is peculiar to aerosol assimilation is that the problem is severely under-constrained due to the fact that several aerosol species have to be constrained with a total column-integrated observation for radiometric measurements or a profile of backscattering for lidar measurements. This implies that there is no one-to-one correspondence between the observations and the control variable. There are various approaches to get around this problem using sensible assumptions. For example, ECMWF formulates the control variable in terms of a total aerosol mixing ratio and distributes the increments from this variable into the single species mixing ratios in order to avoid defining the error statistics for all species, which would be heavily reliant on the model. Other centres, for example, MRI/JMA, use a method where the emission intensity is treated as a poorly known model parameter defined at each model surface grid point and estimated in the analysis. The control vector then consists of the dust emission parameters and model variables such as aerosol concentrations and meteorological components. In the end, it has to be accepted that no matter how complex and sophisticated the aerosol assimilation system is, a lot of the information comes from the *model* rather than the *observations*. This is a special limitation for dust because retrieval is often impossible over the bright deserts that are dust sources.

Even with its limitations, dust forecasts from systems with aerosol analysis have been shown to have reduced bias and improved correlations with respect to independent observations, when compared to forecasts from the same systems with no aerosol analysis, in particular for dust events (Benedetti et al 2009; Zhang et al. 2008). Moreover, aerosol reanalyses, in particular of dust and biomass burning aerosols, are becoming increasingly valued to assess annual and seasonal anomalies and to monitor the state of climate (Benedetti et al. 2013).

10.5   Evaluation of Atmospheric Dust Prediction Models

10.5.1   *General Concepts*

An important step in forecasting is the evaluation of the results that have been generated. This process consists of the comparison of the model results to observations on different temporal and spatial scales. In this framework, there are three primary objectives in forecast evaluation:

1. Assessing the value of the forecast variables. The main goal of the evaluation exercise is to evaluate quantitatively and qualitatively whether the modelling system is successfully predicting the temporal and spatial evolution of a particular process.
2. Determining the suitability of a specific application and configuration. Explore the adequacy and correctness of the science represented in the model for the purposes for which the model is applied. Comparison with other models in addition to the observations can be helpful in identifying the strength and weakness of the system.
3. Guiding improvement. Evaluation results should lead to new directions in model development and improvement

A forecast system is judged by its ability to simulate the spatial and temporal evolution of chosen forecast variables. In this regard, the metric is what drives model development and optimisation. Hence, the evaluation metrics must be chosen carefully.

The first evaluation is done right after the forecast period and depends on observations that are made available shortly after they were taken. This type of evaluation, sometimes referred to as verification, is generally part of the operational forecasting process and is therefore done on a regular basis in near real-time. The end result is the quantification of confidence and predictive accuracy of the model products. An additional and different type of evaluation is where the model's performance to simulate a given event or an annual cycle is examined in depth. This case study evaluation can be made any time after the forecast period, and observations that were not available for the near real-time evaluation can be included. The purpose is to identify potential sources of error in order to improve the model. In both cases, the evaluation process will depend on the intended use of the forecast product.

10.5.2 Observational Data for Evaluation

The first problem in identifying appropriate routine measurements for evaluation of dust models is the scarcity of observations of dust events. The location of the main dust sources in unpopulated areas complicates the establishment of observing networks.

Thus, the first option to address the evaluation of dust models has been the use of satellite products. They have the advantage of a large spatial coverage (regional to global), they are made regularly, and their observations are made available to weather centres and other institutions in near real-time. Shortcomings include satellite measurements' highly integrated nature, not only over the atmospheric column but also over all aerosol components. Therefore, applications involving a particular aerosol type (like dust) might be limited in some cases to seasons and regions, when or where that type dominates the aerosol composition (Basart et al.

2012a). Another limitation is the low aerosol detectability over bright surfaces, which affects instruments operating in the visible part of the spectrum. The new generation of high-resolution IR spectrometers and interferometers on polar orbiting satellite platforms (e.g. AIRS, IASI) has the potential to provide good quality dust information (Hilton et al. 2012). Algorithms are currently being developed and validated (Peyridieu et al. 2010; Klüser et al. 2011), and it is likely that these products will become prominent both for evaluation and assimilation.

Regions with air quality monitoring networks are the main surface data source for point evaluation of dust concentrations predicted by dust models. As with the satellites, air quality measurements integrate the contribution of the different types of atmospheric aerosol. Furthermore, observational values are usually limited to the concentration of particulate matter with an aerodynamic diameter less than 10 μm (PM10), which does not always encompass the full size range of dust particles suspended in the atmosphere. Finally, it is important to consider the selection of stations, since many of them are located in cities, industrial parks or roads, where local human activity is the main source of particles, obscuring the contribution of dust to measured quantities.

Visibility data included in meteorological observations have sometimes been used as an alternative source of information (Shao et al. 2003). Visibility is mainly affected by the presence of aerosol and humidity in the atmosphere. If visibility is recorded manually, illumination is also important for intermediate visibilities. Therefore, the use of visibility data must be complemented with information on present weather to discard those cases where visibility is reduced by the presence of hydrometeors (fog, rain, etc.). Several empirical relationships between visibility and dust surface concentration can be found in the literature (d'Almeida 1986; Ben Mohamed et al. 1992; Shao et al. 2003). However, the validity of these relationships is very limited because the visibility reduction depends not only on the dust mass concentration but also on the size spectrum of particles, as well as their density, chemical and mineralogical composition and atmospheric humidity.

Direct-sun photometric measurements are a powerful remote sensing tool that provides retrieval of column-integrated aerosol microphysical and optical properties. In particular, AERONET is a comprehensive set of continental and coastal sites complemented with several sparsely distributed oceanic stations that provides large and refined data sets in near real-time (Holben et al. 1998; Dubovik and King 2000). AERONET measurements are by far the most commonly used in dust model evaluation. Integral parameters such as AOD are complemented with spectral information, which permit retrieval of aerosol microphysical and composition properties (Dubovik et al. 2002). A major shortcoming of these measurements is their unavailability under cloudy skies and during night-time.

Finally, lidar and the most recent generation of ceilometers permit routine measurement of aerosol vertical profiles. However, continuous measurements in ground-based stations are only performed in a few stations that are, in general, far from the main dust sources. On the other hand, space-borne lidars (e.g. CALIOP) provide global spatial coverage, but their temporal coverage is limited.

Table 10.4 Definitions of common model validation metrics. o_i and m_i are respectively observed and modelled values at time and location i, n is the number of data pairs and $(^-)$ denotes the mean value

Validation metrics	Formula	Range	Ideal score
Mean bias error (MBE)	$\text{MBE} = \dfrac{1}{n}\sum_{i=1}^{n}(m_i - o_i)$	$-\infty$ to $+\infty$	0
Root-mean-square error (RMSE)	$\text{RMSE} = \sqrt{\dfrac{1}{n}\sum_{i-1}^{n}(m_i - o_i)^2}$	0 to $+\infty$	0
Correlation coefficient (r)	$r = \dfrac{\sum_{i=1}^{n}(m_i - \overline{m})\,(o_i - \overline{o})}{\sqrt{\sum_{i=1}^{n}(m_i - \overline{m})^2}\cdot\sqrt{\sum_{i=1}^{N}(o_i - \overline{o})^2}}$	-1 to 1	1
Fractional gross error (FGE)	$\text{FGE} = \dfrac{2}{n}\sum_{i=1}^{n}\left|\dfrac{m_i - o_i}{m_i + o_i}\right|$	0–2	0
Normalised mean bias error (NMBE)	$\text{NMBE} = \dfrac{1}{n}\sum_{i=1}^{n}\left(\dfrac{m_i - o_i}{o_i}\right)$	-1 to $+\infty$ for non-negative variables	0
Normalised root-mean-square error (NRMSE)	$\text{NRMSE} = \sqrt{\dfrac{1}{n}\sum_{i=1}^{n}\left(\dfrac{m_i - o_i}{o_i}\right)^2}$	0 to $+\infty$	0

10.5.3 Metrics

The evaluation typically starts with an analysis of the plots of the forecast values against observations for a particular location. This method, implemented for near real-time monitoring, is very valuable in detecting outliers and identifying jumps in performance. Then, the core of the evaluation process is the computation of metrics defined to provide a quantitative characterisation of the agreement between model results and observations over specific geographic regions and time periods. The most common metrics used to quantify the departure between modelled and observed quantities are described in Table 10.4.

– The BE captures the average deviations between two data sets with negative values indicating underestimation and positive overestimation of the model.
– The RMSE combines both the bias and the standard deviation. It is strongly dominated by the largest values due to squaring. Especially in cases where prominent outliers occur, the usefulness of RMSE is questionable, and the interpretation becomes difficult.
– r indicates the extent to which temporal and spatial patterns in the model match those in the observations.

– The FGE is a measure of the overall model error. It behaves symmetrically with respect to under- and overestimation, without overemphasising outliers.
– The NMBE and NRMSE are dimensionless versions of MBE and RMSE, built to facilitate comparison between the behaviour of different variables.

10.5.4 Examples of Near Real-Time Evaluation

The evaluations of dust forecasts are mainly conducted by the weather centres generating the forecasts or institutions working in collaboration with them. Evaluating the model forecasts against satellite- and ground-based observations is used to detect problems early on and also to provide a first indication of the accuracy of the products to the users. The evaluation systems developed in the framework of the WMO SDS-WAS NAMEE Regional Centre and MACC-II project are presented here.

The WMO SDS-WAS Dust Model Evaluation Initiative

For the evaluation of the WMO SDS-WAS multi-model ensemble, the dust optical depth (DOD) forecast by the models is first drawn together with the AERONET AOD observations in monthly charts for selected dust-prone stations. Then, different evaluation metrics (see Table 10.4) are computed in order to quantify the agreement between predictions and observations for individual stations and different regions (Sahara-Sahel, Middle East and Mediterranean) as well as different temporal scales (monthly, seasonal and annual basis). Comparison statistics are restricted to observations with low Ångström exponent (AE) values (<0.6) to ensure that forecast and observations are only compared during episodes where dust is the largest contributor. However, there will always be a small portion of particles from other sources, so a small negative bias can be expected. Figure 10.4 shows an example of routine verification of the multi-model ensemble products over the AERONET station of Santa Cruz, Tenerife. In this specific example, all models tend to overestimate the DOD for at the beginning of the month, while the dust episodes in mid-August and at the end of the month are better represented with various degrees of skills.

The MACC-II Evaluation

In the evaluation of the MACC-II forecasts, the DOD at 550 nm wavelength forecast by the MACC model are drawn together with the AERONET and MODIS retrievals of AOD in monthly charts for selected stations, as well as the contributions of other aerosol types. However, the scoring metrics that are calculated on a monthly averaged time frame for different regions or stations are always calculated for the
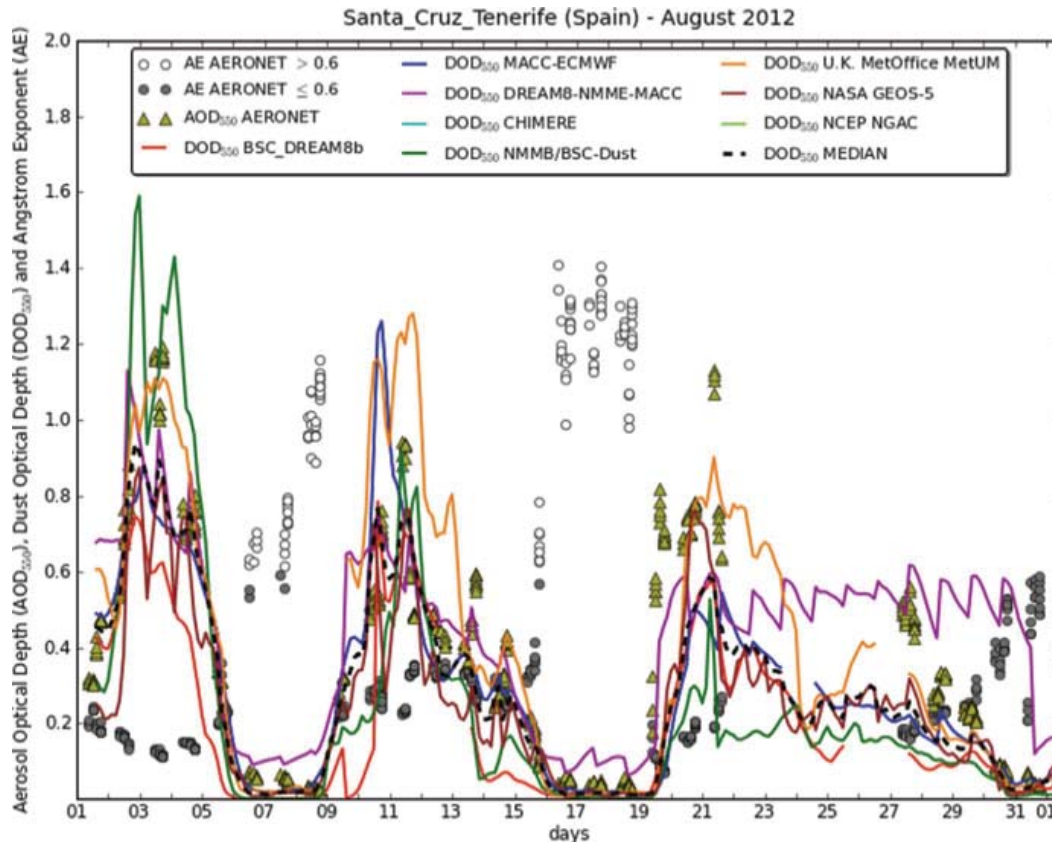
Fig. 10.4 Time series of aerosol optical depth at Santa Cruz de Tenerife (28.5 N, 16.2 W) for August 2012. The plot shows the DOD forecast by the different models (*solid lines*), the median value (*dashed black line*) and direct-sun AERONET observations (*yellow triangles*). An Ångström exponent (*AE*) lower than <0.6 (*dark grey dots*) indicates that the observed AOD is associated with the presence of desert dust

total atmospheric aerosol, without any distinction of the species. This evaluation is complemented with regular reports describing the model performance to forecast major and recent events (available online at www.copernicus-atmosphere.eu).

The calculation of scores is complicated by the geographic inhomogeneity of the observation sites. AERONET sites are not spread evenly over the globe, but are far more concentrated in developed parts of the world such as Europe and the USA. The sites in use are also time-varying, with new sites appearing and old sites disappearing. Taking simple means over the sites therefore leads to scores which reflect the geographic spread of the sites at the time and which are strongly biased towards certain regions.

In order to reduce geographic bias and increase long-term stability, model-versus-AERONET scores are computed using weights for each observation that reflect the local observation density at the observation time. This is done through the calculation of "Voronoi polygons". For a given set of points in space, the Voronoi polygon around a given point is the region closer to that point than any other. At each observation time, the polygons are calculated on the sphere for all available

sites, and the polygon areas are used as the observation weights. Since the polygons will naturally be smaller in data-dense areas, observations in these areas receive lower weights than those in data-sparse areas. To prevent observations in very data-sparse areas receiving higher than reasonable weights, the polygon edges are limited to a maximum radius. This is currently set to a value which results in a maximum polygon area of 1 % of the total area being scored.

Case Study Evaluation

An exhaustive comparison of model outputs against other models and observations can reveal weaknesses of individual models, provide an assessment of uncertainties in simulating the dust cycle and give additional information on sources for potential model improvement. For this kind of study, multiple and different observations are combined to deliver a detailed idea of the structure and evolution of the dust cloud and the state of the atmosphere at the different stages of the event. Observations detailed in Sect. 10.5.2 are usually complemented with strictly meteorological observations such as wind speed and direction at the surface and wind profile within the atmospheric boundary layer.

Multiple case studies concerning a single model can be found in the literature (e.g. Pérez et al. 2006b; Heinold et al. 2007; Cavazos et al. 2009). On the other hand, inter-comparisons of multiple models simulating the same event are described by Uno et al. (2006) and Todd et al. (2008). Both studies reveal the ability of models to reproduce the onset and duration, but not the magnitude of a given dust event. Furthermore, even though the models were able to reproduce surface measurements, large differences existed among them in processes such as emission, transport and deposition. Shao et al. (2003) evaluated not only the model performance to simulate a specific dust event but also the model capacity to predict the event for different lead times. The authors found that the predicted quantities agreed well with the observations. Many global aerosol models have also been evaluated over extended time periods as part of the AeroCom project (see Chap. 9).

10.6   Conclusion

Dust numerical prediction is a growing area of research with many operational applications. In the last few years, many centres have started activities to provide dust forecasts to interested stakeholders, who range from solar energy plant managers to health and aviation authorities, from policymakers to climate scientists. There is also a growing interest in understanding how dust impacts the general circulation of the atmosphere through its radiative effects which could help in improving numerical weather prediction and projections of climate change. Dust forecast models have reached a high degree of complexity and can provide useful information to forecasters. Some factors limiting the accuracy of the models are

related to the complex emission sources and the heterogeneous characteristics of the emitting surfaces, including texture, composition, vegetation type and topography. Dust prediction is also limited by the paucity of observations available for data assimilation, model initialisation and verification. A significant current limitation is that satellite instruments do not precisely distinguish the presence of dust from that of other aerosol species. As more products from satellite- and ground-based stations become available, it is foreseeable that dust prediction will improve. In order to provide the best dust forecasts possible, along with improving the dust models, there are currently international efforts to bring together several operational and quasi-operational models to form multi-model ensembles. The merit of these ensembles is to bring together the strengths of the various state-of-the-art models while offering the possibility to approach the dust prediction from a probabilistic perspective, thus enhancing the range of applications. The development of these multi-model ensembles is at an early stage, and exploitation of their potential is still limited, also because of the relatively small number of participating models. However, it is anticipated that the probabilistic approach to dust prediction both at level of the individual centres and within the context of the multi-model ensembles will become more important in the future.

Appendix A: Technical Aspects of Data Assimilation for Dust Prediction

A10.1 Assimilation Techniques

Variational Methods (CMA, ECMWF, FNMOC/NRL, Met Office, NASA GMAO)

The variational method is a well-established approach that combines model background information with observations to obtain the "best" initial conditions possible. In the 2D- and 3D-Var versions, the fields are adjusted at the analysis time whereas in 4D-Var, a short-term forecast is run over the selected time window (usually 12 h) to provide a so-called first guess. In 4D-Var, the dynamical model is then used as a strong constraint to minimise the difference between the model background and the observations. This approach is widely used in many NWP centres. The fundamental idea of the variational methods is based on minimisation of a cost function which measures the distance between observations and their model equivalent, subject to a background constraint usually provided by the model itself. Optimisation of this cost function is performed with respect to selected control variables (e.g. the initial conditions). Adjustments to these control variables allow for the updated model trajectory to match the observations more closely. Assuming the update to the initial condition is small, an incremental formulation can be adopted to ensure a good compromise between operational feasibility and physical

consistency in the analysis (Courtier et al. 1994). This so-called "incremental" approach is employed at ECMWF. Another key aspect of the variational methods is the use of the *adjoint* model to calculate the gradient of the cost function needed in the minimisation. Coding an adjoint of highly nonlinear parameterisations can be involved, and the parameterisations may need to be linearised before an adjoint can be constructed.

Kalman Filter and Ensemble Kalman Filter Methods (MRI/JMA, NRL)

Another data assimilation method, the Kalman filter (KF), has been well known since the 1960s (Kalman 1960). KF, which is based on the linear minimum variance estimation approach, evolves the error covariance matrix temporally. The KF calculation requires neither tangent linear models nor adjoint models. Despite these advantages, KF requires the inverse calculation of the matrices with the dimensions of the model state space. The size of the model state space in geosciences is often of the order of millions: for such large systems, KF cannot be adopted. In order to exploit the advantages of KF and reduce the computational burden, the ensemble Kalman filter (EnKF) was developed (Evensen 1994, 2007). The basic concept of EnKF is that the ensemble of the forward model forecasts is able to represent the probability distribution function (PDF) of the system state and approximate the error covariance distribution. The EnKF is mathematically equivalent to the original Kalman filter, under the ideal conditions where the simulation model is linear, and the EnKF employs an infinite ensemble size. In the MRI/JMA aerosol assimilation system, a 4D expansion of the EnKF (4D-EnKF) is adopted to assimilate asynchronous observations at the appropriate times. Using the 4D-EnKF aerosol assimilation system, the surface emission intensity distribution of dust aerosol is estimated (Sekiyama et al. 2010, 2011). The vector augmentation mentioned above enables EnKF to estimate the parameters through the background error covariance between dust emissions and observations. Consequently, EnKF simultaneously estimated the aerosol concentrations (as model variables) together with the dust aerosol emission intensity (as model parameters). The MRI/JMA aerosol assimilation system employs the local ensemble transform Kalman filter (LETKF), which is one of the EnKF implementation schemes (Hunt et al. 2007). The LETKF uses the ensemble transform approach (Bishop et al. 2001) to obtain the analysis ensemble as a linear combination of the background ensemble forecasts. The LETKF handles observations locally in space, where all the observations are assimilated simultaneously.

It is important to note that 4D-Var and ensemble Kalman filter methods approximately converge, when 4D-Var is run over a long assimilation window (e.g. 24 h) and model error is included, as they are both based on the Bayes theorem which postulates that the probability distribution of the analysis errors is a linear combination of the probability distribution of the observations and background errors (Fisher et al. 2005).

A10.2   Observations Used for the Dust Analyses

Main Products

The MODIS AOD product is used most widely due to its reliability and availability in near real-time (Kaufman et al. 1997; Remer et al. 2005). Two separate retrievals with different accuracies are applied over land and ocean. The former suffers from higher uncertainties due to the impact of the surface reflectance. Several other factors affect the accuracy of the retrievals both over land and ocean: cloud contamination, assumptions about the aerosol types and size distribution, near-surface wind speed, radiative transfer model biases and instrumental uncertainties (Zhang and Reid 2006). The MODIS product provides the total AOD, such that the partitioning between dust and other aerosol species is driven by the particular analysis system and its underlying model. However, the standard MODIS Dark Target method does not deliver data over bright surfaces where there is not enough contrast between the surface and overlying aerosol layer. However, iron in desert soils absorbs at blue wavelengths, and albedo in the blue part of the solar spectrum is considerably darker than the mid-visible and red. This allowed the development of the MODIS Deep Blue product (Hsu et al. 2004, 2006). Deep Blue is not currently assimilated at NRL, NASA or ECMWF, but it is expected to be incorporated into their systems now that an error matrix has been established (Shi et al. 2012).

At the Met Office, the standard MODIS and MODIS Deep Blue (Hsu et al. 2004, 2006; Ginoux et al. 2010) products are being assimilated, and the AOD products at 550 nm wavelength from SEVIRI from Brindley and Ignatov (2006) and Brindley and Russell (2009) are being monitored prior to being assimilated in the near future. However, only a subset of observations can be used, as the forecast model contains only dust rather than a full suite of aerosols. This restriction is achieved by geographic filtering of the SEVIRI AOD and by using the MODIS standard product aerosol-type flags over land and preferentially using the MODIS Deep Blue product over bright desert surfaces. The presence of other aerosols in these regions of high dust loading introduces uncertainty into the assimilation process.

CALIPSO (e.g. Winker et al. 2007) is the first satellite mission to have made aerosol lidar observations routinely available from space. At MRI/JMA, the CALIPSO Level 1B data have been successfully assimilated into the JMA dust forecast model with a positive impact on the prediction of aeolian dust. A derived CALIPSO product is also assimilated at NRL (Campbell et al. 2010; Zhang et al. 2011). In particular, Zhang et al. (2011) found that assimilation of lidar data had a beneficial impact on the 48 h forecast. The same product is under study for assimilation at ECMWF.

Data Quality Aspects and Bias Correction

Perhaps the most pressing issue for satellite data assimilation is the development of appropriate satellite error models. Indeed, a key assumption in data assimilation is that the observation errors are uncorrelated spatially. For satellite aerosol products, and dust products in particular, there is considerable spatially correlated bias. Such bias is formed from a number of factors, including biases in the algorithm's lower boundary condition/surface reflectance, microphysical bias in the assumed optical model of the aerosol particles and the cloud mask. These biases can lead to unphysical analysis fields, which in turn can lead to positive or negative perturbation "plumes" in forecast fields. Currently, satellite data providers do not generate prognostic error models, and it has fallen on the data assimilation community to modify the products for their own purposes. Debiasing data products and developing reliable point-by-point uncertainties are time-consuming. Further, aerosol product algorithms update frequently, leaving previous error analyses obsolete.

Each centre's development team has approached satellite data quality and bias correction differently. Development for FNMOC systems at NRL and the University of North Dakota has favoured extensive error analysis at the expense of sophistication in the data assimilation technology. MODIS over ocean, land and Deep Blue products have had extensive debiasing based on comparison with AERONET observations and error modelling applied (Zhang and Reid 2006; Shi et al. 2011a, 2012; Hyer et al. 2011). In addition, the spatial covariance of the MODIS and MISR products has also been undertaken (Shi et al. 2011b). Internal studies at NRL have shown that, overall, the assimilation of raw satellite aerosol products boosts model verification scores. After a set of quality assurance steps were taken with the satellite products, NAAPS root-mean-square error (RMSE) improved by more than 40 %. Lidar assimilation has taken a similar method, with considerable quality assurance (QA) checks (Campbell et al. 2010).

At ECMWF, a variational bias correction is implemented based on the operational set-up for assimilated radiances following the developments by Dee and Uppala (2009). The bias model for the MODIS data consists of a global constant that is adjusted variationally in the minimisation based on the first-guess departures. Although simple, this bias correction works well in the sense that the MACC analysis is not biased with respect to MODIS observations. Moreover, this approach has the advantage of being tied to the optimisation of the cost function, and as such it is estimated online, not requiring previous preprocessing of the observations. The bias error model allows more complex treatment with the addition of other bias predictors that are relevant for AOD, for example, instrument geometry, viewing angle, cloud cover, wind speed, etc. Improvements to the bias model are currently being undertaken.

A10.3   Definitions of Background and Observational Errors

Since the relative weight between the background and the observations is decided by the error statistics prescribed for both, in areas that are data-limited such as the deserts, the aerosol analysis is severely under-constrained relative to the observations and relies almost entirely on the background. Also, the background matrix is responsible for the redistribution of the aerosol information from the observations to the model fields. This is again especially true for dust due to the already-mentioned paucity of observations over bright surfaces.

Background Error Covariance Matrices

The aerosol background error covariance matrix used for aerosol analyses at ECMWF was derived using the Parrish and Derber method (also known as NMC method; Parrish and Derber 1992) as detailed by Benedetti and Fisher (2007). This method was long used for the definition of the background error statistics for the meteorological variables and is based on the assumption that the forecast differences between the 48 h and the 24 h forecasts are a good statistical proxy to estimate the model background errors. The advantage in using the model to define the errors is the grid-point availability of the statistics over a long period. This leads to a satisfactory background error covariance matrix without the need to prescribe the vertical and horizontal correlation length as shown in Kahnert (2008). However, a shortcoming of this method consists in the static definition of the background error covariance matrix, which can lead to suboptimal analysis in the case of unusual situations such as intense storms. This is addressed by the ensemble methods with flow-dependent error estimates which suit the specific situation ("errors of the day").

For the FNMOC/NRL NAAPS global model, background error covariances were estimated in a number of methods, all converging to the same number for the error covariance length (250 km, the same as is commonly assumed for water vapour). This length was determined from experiments from the MODIS data set. As a check, error covariances were also estimated from a 3-month simulation from the 20-member NAAPS ensemble driven purely from the NOGAPS meteorological ensemble.

Flow-Dependent Background Error Covariance Matrix

"Errors of the day" can be estimated in the context of the ensemble methods, where at each analysis time, a series of forecasts is run starting from perturbed conditions, and these forecasts provide an estimate of the model errors. However, the EnKF tends to be easily influenced by sampling errors at long distances because the available ensemble size is too small to estimate the background error covariance of the atmospheric system. Therefore, a covariance localisation must be applied

for all the EnKF implementation schemes to reduce the spurious impact of distant observations. The LETKF permits a flexible choice of observations to be assimilated at each grid point. For example, the MRI/JMA system employs the covariance localisation with a Gaussian weighting function that depends on the physical distance between the grid location and the observation. The limited ensemble size causes both sampling errors at long distances and filter divergence. To compensate for the error underestimation and avoid the filter divergence, it is necessary to increase the ensemble spread every data assimilation cycle. This technique is called covariance inflation. The MRI/JMA system utilises a multiplicative inflation method, in which the ensemble spread is uniformly multiplied by a constant value larger than one; it is common to tune this inflation factor empirically. Furthermore, adding random perturbations to the initial state of each ensemble member is sometimes necessary to maintain the diversity of the ensemble members and not to lose the error covariance among the model variables. In the MRI/JMA system, random perturbations are added to dust emission intensity. This type of flow-dependent background error definition is very promising, and it has also been progressively adopted for standard meteorological applications in variational systems through the so-called hybrid approach (Buehner et al. 2010a, b; Clayton et al. 2012), in which the assimilation framework is variational, but the background errors of the day are defined through ensemble methods. This approach should work well for dust initialisation, where the errors on the dust prediction are both associated to emission uncertainties and transport.

Observation Errors

The problem of defining appropriate errors for the observations when those are *retrieval products* is very complex. Observation errors for these products are comprised of measurements errors that depend on instrument calibration and characteristics and a priori and representativeness errors that depend on the retrieval assumptions regarding the parameters that are not directly observed but that affect the retrieval output, such as the optical properties assumed for the aerosols, as well as on the overall quality of the forward model used in the retrieval. Most satellite data providers do not provide errors at the pixel level, but rather provide regression parameters derived from comparison of the satellite products with ground-based equivalent products like AERONET retrievals of AOD which are deemed to have high accuracy. This type of regression-based error estimate does not faithfully represent the accuracy of the retrieved product at the level of individual pixels, which is what is needed in data assimilation. Often the developers end up assigning their own errors to the observations to be able to fit the needs of their system. For example, at ECMWF, the observation error covariance matrix is assumed to be diagonal, to simplify the problem. The errors are also chosen ad hoc and prescribed as fixed values over land and ocean for the assimilated observations (MODIS AOD at 550 nm). This was decided after investigation revealed that biases were introduced in the analysis due to the observation error assumptions when those were specified

as *relative* rather than absolute errors. While this might be a specific characteristic of the ECMWF system, the problem of a correct specification of the pixel-level errors on aerosol-retrieved products is a topic of ongoing research (Kolmonen et al. 2013).

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