AWARE Task 4. Overview of forecast methods, representation and user-oriented products linked to HIW

Task 4.1. Postprocessing vs. direct model output for HIW

Part 1. Overview of for forecast

Yu. Khlestova and E. Tatarinovich (RHM)

The fog is suspended cloud particles in the air near the surface (height 1.5-2 m), which reduces horizontal visibility up to 1 km and less (Khrgian and Mazin, 1989). The main reasons of fog formation are the air mass advection, radiative cooling due to cloudless meteorological conditions, orography effects and anthropogenic activity. Anthropogenic activity stimulates an increase of cloud condensation nuclei number concentration and promotes cloud formation. The most complete fog forecast includes the time of fog formation and duration, its vertical extent and intensity. The fog vertical extent and fog duration depend on atmospheric moisture content and specific meteorological conditions (air stratification, wind speed, cloud amount and structure). Fogs along the vertical extent are divided into ground level (below 2 m), low (2-10 m), medium (1-100 m) and high (more 100 m) fog (Khrgian and Mazin, 1989).

The horizontal visibility (VIS) is the main characteristic of fog intensity. VIS is based on the Koschmieder's formula (Koschmieder H., 1924):

$$VIS = \frac{-\ln(\varepsilon)}{\beta_\lambda},$$

where ε is the eye contrast sensitivity threshold (usually 0.05 or 0.02) (ICAO, 2010; Stoelinga and Warner, 1999), β is the extinction coefficient, λ is the irradiance wavelength, which is usually equal to 550 nm (Trautmann and Bott, 2002). The theoretical formulation of β is based on Mie theory:

$$\beta_\lambda = \int_0^\infty Q_{ext,\lambda} n(r) r^2 \, dr,$$

where Q_{ext} is Mie efficiency factor, r is the radius of cloud droplets, n(r) is the number density of cloud droplets (Gultepe and Milbrandt, 2007). The Mie efficiency factor is about 2 for cloud and rain droplets (Koening, 1971). The theoretical equation of β is not used in the operational forecast. Firstly, the theoretical formulation is expensive for operational weather prediction. Secondly, the theoretical formulation of extinction coefficient requires a more detailed description of cloud droplet's number density. The extinction parameter can also be parameterized using standard meteorological values or microphysical cloud characteristics. There are three main approaches to fog prediction using parametrization. According to the first approach, visibility can be forecasted using empirical relations between β and meteorological parameters (air temperature, dew point temperature, wind speed, air pressure) by observation.

Empirical ratios are created for specific points (specific climate and orography) and synoptic situations. This method requires a preliminary analysis of meteorological conditions, since empirical relations are found for specific air conditions and fog physical mechanisms.

The second approach is the use of fog forecasting techniques based on machine learning methods (Abdulkareem K. H. et al., 2019; Zhu et al., 2017; Oguz and Pekin, 2019). The input data is observed or simulated air temperature, dew point temperature, atmospheric pressure, relative humidity, wind speed and direction at 10 m. ML methods organize the forecast based on a set of air condition data. The result is the extinction coefficient or visibility.

According to the third approach, the extinction coefficient can be calculated using β parametrization and numerical weather prediction results (directly in the model or in postprocessing). All parametrizations are obtained based on observations. There are two types of numerical visibility prediction: the meteorological approach and the microphysical approach. The extinction coefficient is based on meteorological characteristics according to the meteorological approach. Examples of "meteorological approach" parametrizations with its applications are shown in Table 1. The T is the air temperature (°C), T_d is the dew point temperature (°C), RH is the relative humidity (%), $a_{1\text{-}8}$ are constants based on measurement data. The main limitation of the meteorological approach is that meteorological values are not able to describe the cloud structure, which reduces the forecast accuracy.

Table 1. The meteorological approach of extinction coefficient

Parametrization of β and VIS, км	Source	Application
$\beta = 6000\dfrac{T - T_d}{RH^{1.75}}$	Doran et al., 1999	Forecast System Laboratory
$VIS = a_1 \ln(RH) + a_2$ $VIS = a_3 RH^{a_4} + a_5$ $VIS = a_6 RH^2 + a_7 RH + a_8$	Gultepe et al., 2009	
$VIS = 60000 exp\left(\dfrac{-2.5}{80}(PH - 15)\right)$	Bang et al., 2009	

The microphysical approach of β is based on cloud characteristics. The microphysical parametrizations are shown in Table 2. The N_c is the number concentration of cloud droplets (cm^{-3}), N_i is the number concentration of ice particles (cm^{-3}), QC is the liquid water content (g/m^3), QI is the ice water content (g/m^3), R is the radius of cloud droplets (m), $b_{1\text{-}3}$ are constants based on measurement data.

The relation (Stoelinga and Warner, 1999) is operatively used for numerical weather forecasting in the WRF model (Weather Research and Forecasting Model). The parametrization of β(Kunkel B.A., 1984) is based on (Eldridge R.G., 1966; Eldridge R.G., 1971; Pinnick et al., 1978; Tomasi and Tampieri, 1976) works and is widely used in HARMONIE (HIRLAM ALADIN Research on Meso-scale Operational NWP In Europe), AROME (Applications of Research to Operations at Mesoscale) and is also applied to the one-dimensional fog forecast model COBEL. The β-description of the PAFOG fog prediction model is based on (Trautmann and Bott, 2002). The fog forecast in Unified Model uses the method (Clark et al., 2008).

Table 2. The microphysical approach of extinction coefficient

Parametrization of β and VIS, км	Source	Application
$\beta = b_1 QC^{b_2}$	Eldridge R.G., 1966; Eldridge R.G., 1971; Pinnick et al., 1978; Tomasi and Tampieri, 1976	Kunkel B.A., 1984
$\beta = 144.7QC^{0.88}$	Kunkel B.., 1984	COBEL (Muller M.D., 2006); HARMONIE (Kettler T.T., 2020); AROME (Philip et al., 2016); WRF (Creighton et al., 2014); Texeira et al., 2001
$\beta = 163.9QI$	Stoelinga and Warner, 1999	WRF (Creighton et al., 2014); HARMONIE (Kettler T.T., 2020)
$\beta = 230\dfrac{R}{QC}$	Zverev A.S., 1977	Shatunova et al., 2015
$\beta = 1.5\pi N_c R^2$	Clark et al., 2008	UM (Claxton et al., 2008; Boutle et al., 2016)
$\beta = b_3 QC^{2/3} N_c^{1/3}$	Bott and Trautmann, 2002	PAFOG

The visibility forecast within the numerical weather prediction can be improved using one-dimensional fog models (1D) and specific settings of model physics. Well-known 1D models are the University of Toulouse COBEL model (Couche Brouillard Eau Liquide) (Bergot and Guedalia, 1994; Muller M.D., 2006; Muller et al., 2007) and the PAFOG (PArameterized FOG) model of the University of Bonn (Bott and Trautmann, 2002; Masbou M., 2008; Mohr et al., 2009). Thermodynamic, radiative and microphysical processes of 1D models are presented with higher vertical resolution, especially in the planetary boundary layer. The lower vertical grid spacing promotes to improve the description of turbulent fluxes and radiative cooling in fog conditions (Trautmann and Bott, 2002a-b).

Thus, the operational VIS prediction is usually based only on one-moment microphysics results (liquid and ice water contents). However, we can also account for the number concentration of particles using two-moment microphysics. The two-moment microphysics implementation and aerosol representation lead to a more sufficient cloud description and fog.

Finally, the detailed tuning of model physical schemes is required to improve the fog forecast. For example, the formation of stable atmospheric stratification is assumed for radiative fog formation, and this is necessary to reduce the errors of the simulated turbulent heat transfer (Thoma and Bott, 2011; Masbou and Bott, 2010). The time of fog formation and dispersion depends on the model description of radiation processes (Antoine S., 2020). Schemes of fog prediction, including the aerosol physical properties and dynamics and cloud-aerosol interaction, show more sufficient results (Vie et al., 2015; Clark et al., 2008).

It can be concluded that the quality of fog prediction depends mainly on the model grid spacing and the approaches of turbulent, microphysical, radiative processes and surface-air exchanges. The fog prediction tasks today have two basic directions. Firstly, we need to decrease the model grid spacing due to the locality and spatial heterogeneity of fog events (Boutle et al., 2016; Philip et al, 2016). And, secondly, the lower grid spacing requires a revision of model physics, new approaches and description of urban environment (Roebber et al., 2004; Zangl G., 2021).

Список литературы

1. International Civil Aviation Organization. (2010). Meteorological Service for International Air Navigation. Annex 3 to the Convention on International Civil Aviation. Part I Core SARPs. Part II Appendices and Attachments. ICAO.
2. Creighton, G., Kuchera, E., Adams-Selin, R., McCormick, J., Rentschler, S., & Wickard, B. (2014). AFWA diagnostics in WRF.
3. Kettler, T. T. (2020). Fog forecasting in HARMONIE: a case study to current issues with the overestimation of fog in HARMONIE. (Master's thesis).
4. Khrgian, A. Kh., & Mazin, I. P. (Eds). (1989). Clouds and cloudy atmosphere. The handbook. Hydrometeoizdat, Leningrad. In Russian.
5. Abdulkareem, K. H., Mohammed, M. A., Gunasekaran, S. S., Al-Mhiqani, M. N., Mutlag, A. A., Mostafa, S. A., ... & Ibrahim, D. A. (2019). A review of fog computing and machine learning: concepts, applications, challenges, and open issues. IEEE Access, 7, 153123-153140.
6. Bang, C. H., Lee, J. W., & Hong, S. Y. (2008). Predictability experiments of fog and visibility in local airports over Korea using the WRF model. Journal of Korean society for atmospheric environment, 24(E2), 92-101.

7. Bergot, T., & Guedalia, D. (1994). Numerical forecasting of radiation fog. Part I: Numerical model and sensitivity tests. Monthly Weather Review, 122(6), 1218-1230.
8. Bott, A., & Trautmann, T. (2002). PAFOG—A new efficient forecast model of radiation fog and low-level stratiform clouds. Atmospheric Research, 64(1-4), 191-203.
9. Boutle, I. A., Finnenkoetter, A., Lock, A. P., & Wells, H. (2016). The London Model: forecasting fog at 333 m resolution. Quarterly Journal of the Royal Meteorological Society, 142(694), 360-371.
10. Clark, P. A., Harcourt, S. A., Macpherson, B., Mathison, C. T., Cusack, S., & Naylor, M. (2008). Prediction of visibility and aerosol within the operational Met Office Unified Model. I: Model formulation and variational assimilation. Quarterly Journal of the Royal Meteorological Society, 134(636), 1801-1816.
11. Claxton, B. M. (2008). Using a neural network to benchmark a diagnostic parametrization: the Met Office's visibility scheme. Quarterly Journal of the Royal Meteorological Society, 134(635), 1527-1537.
12. Doran J.A., Roohr, P.J., Beberwyk, D.J., Brooks, G.R., Gayno, G.A., Williams, R.T., Lewis, J.M. & Lefevre, R.J. (1999). The MM5 at the air Force Weather Agency – New products to support military operations. The 8th Conference on Aviation, Range, and Aerospace Meteorology, Dallas, Texas, 10-15 January.
13. Eldridge, R.G., (1966). Haze and fog aerosol distributions. J. Atmos. Sci., 28, 605-613.
14. Eldridge, R.G., (1971). The relationship between visibility and liquid water content in fog. J. Atmos. Sci28, 1883-1186.
15. Gultepe, I., & Milbrandt, J. A. (2007). Microphysical observations and mesoscale model simulation of a warm fog case during FRAM project. In Fog and Boundary Layer Clouds: Fog Visibility and Forecasting (pp. 1161-1178). Birkhäuser Basel.
16. Gultepe, I., Pearson, G., Milbrandt, J. A., Hansen, B., Platnick, S., Taylor, P., ... & Cober, S. G. (2009). The fog remote sensing and modeling field project. Bulletin of the American Meteorological Society, 90(3), 341-360.
17. Kahraman, O. Ğ. U. Z., & Pekin, M. A. (2019). Predictability of fog visibility with artificial neural network for Esenboga airport. Avrupa Bilim ve Teknoloji Dergisi, (15), 542-551.
18. Koening, L.R. (1971). Numerical experiments pertaining to warm-fog clearing. Mon. Wea. Rev., 9, 227-241.
19. Koschmieder, H. (1924). Theorie der horizontalen Sichtweite. Beitrage zur Physik der freien Atmosphare, 33-53. In German.
20. Kunkel, B. A. (1984). Parameterization of droplet terminal velocity and extinction coefficient in fog models. Journal of Applied Meteorology and Climatology, 23(1), 34-41.
21. Masbou, M. (2008). LM-PAFOG: a new three-dimentional fog forecast model with parametrised microphysics (Doctoral dissertation, Université Blaise Pascal-Clermont-Ferrand II). 188 pp.
22. Mohr, C., Alberts, I., Masbou, M., & Bott, A. (2009). Nebelbildung am Flughafen München: Klimatologie und Modellierung. Report Universität Bonn. 77 pp.
23. Müller, M. D., Masbou, M., Bott, A., & Janjic, Z. (2005, September). Fog prediction in a 3d model with parametrized microphysics. In WWRP Int. Symp. on Nowcasting and Very Short-Range Forecasting, WWRP.
24. Muller, M.D., Schmutz, C., & Parlow, E. (2007). A One-Dimensional Ensemble Forecast and Assimilation System for Fog Prediction. Pure and Apllied Geophysics, 164, 1241-1264.

25. Philip, A., Bergot, T., Bouteloup, Y., & Bouyssel, F. (2016). The impact of vertical resolution on fog forecasting in the kilometric-scale model arome: a case study and statistics. Weather and Forecasting, 31(5), 1655-1671.
26. Pinnick, R.G., Hoihjelle, D.L., Fernandez, G., Stenmark E.B., Lindberg J.D., Hoidale G.B., & Jenings, S.G. (1978). Vertical structure in atmospheric fog and haze and its effect on visible nd infrared extinction. J. Atmos. Sci., 35, 2020-2032.
27. Roebber, P.J., Schultz, D.M., Colle, B.A., & Stensrud, D.J. (2004). Toward improved prediction: High-resolution and ensemble modeling systems in operations. Weather and forecasting, 19(5), 936-949.
28. Shatunova, M. V., Rivin, G. S. & Rozinkina, I. A., (2015). Visibility forecasting for February 16-18, 2014 for the region of the Sochi-2014 Olympic Games using the high–resolution COSMO-Ru1 model. Russian Meteorology and Hydrology, 40(8), 523-530.
29. Stoelinga, M. T., & Warner, T. T. (1999). Nonhydrostatic, mesobeta-scale model simulations of cloud ceiling and visibility for an East Coast winter precipitation event. Journal of Applied Meteorology and Climatology, 38(4), 385-404.
30. Teixeira, J., & Miranda, P. M. (2001). Fog prediction at Lisbon airport using a one-dimensional boundary layer model. Meteorological Applications, 8(4), 497-505.
31. Tomasi, C., & F. Tampieri, (1976). Features of the proportionality coefficient in the relationship between visibility and liquid water content in haze and fog. Atmosphere, 14, 61-76.
32. Trautmann, T., & Bott, A. (2002a). A numerical model for local fog prediction. Part 1: Parameterized microphysics and radiation. Scientific reports from the Institute of Meteorology at the University of Leipzig, 26, 1-15. In German.
33. Trautmann, T., & Bott, A. (2002b). A numerical model for local fog prediction. Part 2: Handling of soil and vegetation. Scientific reports from the Institute of Meteorology at the University of Leipzig, 26, 16-30. In German.
34. Zangl, G. (2021). News on ICON-MWP. Recent model improvements and systematic resolution-dependence tests to determine needas for further development. 23rd COSMO General Meeting, 14-17 September (teleconference).
35. Zhu, L., Zhu, G., Han, L., & Wang, N. (2017). The application of deep learning in airport visibility forecast. Atmospheric and Climate Sciences, 7(03), 314.
36. Zverev A.S., (1977). Sinoptic meteorology. Hydrometeoizdat, Leningrad. In Russian.