2.2 集合模式输出统计

Gneiting et al.（2005）最早提出基于正态分布的集合模式输出统计模型，应用于气温和海平面气压的预报，得到了预报技巧更高的确定性预报和校准更好的概率密度函数。对于气温等正态分布的变量，EMOS 预测 PDF 可表示为：

$$p(y|M_1,\ldots,M_K)\sim N(a+b_1M_1+\cdots+b_KM_K,c+dS^2) \tag{9}$$

$a+b_1M_1+\cdots+b_KM_K$表示正态分布的均值，$c+dS^2$代表方差，S^2为集合方差。EMOS 模型参数$\theta=(a,\boldsymbol{b},c,d)$可以通过在训练期优化适当的检验指标（如连续等级概率评分、最大似然估计）计算得到。

Scheuerer（2014）将广义极值（generalized extreme value，GEV）分布与集合模式输出统计模型相结合，对 2011 年德国 6 小时累积降水进行预报研究。GEV EMOS 可以产生校准和锐利的概率密度函数分布，并优于扩展逻辑回归和贝叶斯模式平均。此外，在 GEV EMOS 模型中加入邻域信息可以进一步提高概率预报水平。Baran and Nemoda（2016）提出基于截断位移 gamma（censored and shifted gamma，CSG）分布的集合模式输出统计（CSG EMOS）方法，通过向左移动 gamma 分布将零降水量和非零降水的连续 PDF 同时考虑在内：

$$p(y)=\frac{\left(\frac{y-\eta_k}{\beta_k}\right)^{\alpha_k-1}\exp\left(-\frac{y-\eta_k}{\beta_k}\right)}{\beta_k\Gamma(\alpha_k)} \tag{10}$$

其中，α_k和β_k分别是 gamma 分布的形状参数和尺度参数，$\eta_k<0$为位移参数，表示将 CDF 向左移动，将无降水的情况考虑在内。CSG EMOS 模型预报结果在概率校准和逐点降水量预报方面略优于 GEV EMOS，并且整体优于原始集合预报和 BMA 模型。

对于风速，Thorarinsdottir and Gneiting（2010）提出采用在零处截断的正态分布（truncated normal，TN）来解决预测变量非负的问题。Lerch and Thorarinsdottir（2013）将广义极值分布（GEV）与 EMOS 模型相结合以提高德国逐日最大风速预报水平。但该模型存在将正概率分配给负风速的缺点，因此 Baran and Lerch（2015）提出了对数正态分布（log-normal，LN）EMOS 预测风速模型。随后，Baran and Lerch（2016）将截断正态分布与对数正态分布相结合，表明 TN-LN EMOS 组合模型进一步提高了风速概率预报准确率，并且更好地校准了原始集合预报，优于 TN EMOS 和 LN EMOS 模型。

总体而言，BMA 和 EMOS 模型均可以提高天气预报准确率，优于原始集合预报、气候预报等，并且两个模型在多个天气要素预报方面各有长短（Javanshiri et al.，2021；Ji et al.，2021）。尤其是对于降水，相比于将零处正概率与单独的非负分布组合在一起的 BMA 模型，EMOS 模型对在零处的某个适当连续分布进行左删使得零降水的概率可以直接从相应的 CDF 中得出。然而，BMA 和 EMOS 两种方法都特别依赖于参数预测分布，这意味着必须提前指定预测分布并估计其参数。另外，BMA 模型参数多于 EMOS 模型，因此需要足够多的样本数据来训练 BMA 模型以防止出现过度拟合的情况。目前国内对 BMA 的应用研究较多，关于 EMOS 模型的应用还相对较少。

3 讨论和结论

近年来，各种多模式集成技术得到快速发展，已成为国际上领先的气象服务机构广泛使用的提高模式预测准确率的非常有效的后处理统计方法。多模式集成算法不仅减小了由于模式初始条件、物理参数化、动力框架等所带来的预报误差，且计算过程相较于模式积分计算更为简洁高效，提供了巨大的潜在经济效益（Krishnamurti et al.，2016）。本文针对地面气象要素（气温、降水、风）从确定性预报和概率预报两个角度介绍了多种应用范围较为广泛的等权和不等权的多模式集成方案。

简单集合平均和消除偏差集合平均计算简单，但赋予所有模式相同的权重而忽略了模式之间预报性能的差异。不等权的多模式集成如超级集合则充分地考虑了模式差异性，预报技巧较高的模式将被赋予较大的权重，从而能够更加充分有效地利用多模式预报信息。通常，不等权的多模式集成预报技巧优于等权多模式集成。

不同多模式集成方案依然存在一些共性问题，需要进一步探索。例如参与多模式集成的模式个数需要多少才足够？是否越多越好？若剔除预报技巧相对较低的模式，能否进一步提高集成预报技巧？如Johnson et al.（2014）分别用13和11个全球耦合模式对1982–2001年进行季节气候超级集合预测，结果表明在去除预报技巧最低的2个模式后，超级集合的预报评分得到了提升。此外，训练期的长度或是训练期内多少样本才能使权重稳定？如果参与多模式集成的成员模式的动力或物理在训练期和预报期发生变化，那么在训练期得到的权重则不能充分地代表模式行为，也许会导致多模式集成预报技巧不如单模式。滑动训练期的应用在一定程度上能够减小此类负面影响，是否还有别的更好的选择也值得研究。

基于降水对象的多模式集成确定性预报模型，着重考虑了面积、长宽比、轴角和质心位置这四个对象属性。但随着分辨率的增加，降水结构变得越来越复杂，降水对象的形状等特征很难在高分辨率下定义，或者长宽比、轴角这两个属性不足以描述降水对象的形状。在今后的研究工作中，可以尝试将更多的对象属性考虑其中。并且，除MODE空间检验外，也可以尝试使用基于模糊检验的分数技巧评分（Fraction Skill Score，FSS；Roberts and Lean，2008）作为多模式集成模型计算权重的指标。此外，如何构建基于要素对象的多模式集成概率预报模型，以概率的形式预报高温、强降水、大风区的位置、范围等对气象防灾减灾具有重要意义。

已有研究对降水进行雨量分级多模式集成预报（Ji et al.，2019；Qi et al.，2021），同样也可以研究风速的分级预报，有利于对流性大风、气旋性大风等灾害性大风的预报预警。在分级预报中，通常强降水或强风的样本有限，可以通过空间窗口增加格点/站点来扩大目标格点/站点的样本量（Hamill et al.，2017；Lyu et al.，2021）。同时，也可以根据不同区域的气候特征，将研究范围划分成多个子区域。同一区域内的所有格点/站点的预报信息共同组成训练样本以扩充样本量，则同一域内不同格点/站点具有相同的模型参数，而不同区域模型参数则不同（Zhu et al.，2015）。

近年来，计算机技术的发展促进了机器学习相关理论的发展和完善。其中，神经网络作为深度学习模型的一种，受到广泛关注。大气是非线性的，而神经网络对于数据间非线性的关系具有较好的拟合效果。研究表明，随机森林、长短期记忆神经网络（Long Short-Term Memory，LSTM）、U-Net等机器学习模型比频率匹配、集合伪偏差校正等传统方法能更好地对温压风湿等气象要素进行订正（Li et al.，2019；Han et al.，2021）。随着机器

学习的发展，可以尝试将神经网络、支持向量机等方法与多模式集成技术相结合，以进一步提高天气预报技巧。雷彦森等（2018）研究发现基于遗传算法优化的BP神经网络的多模式集成对地面气温的预报比超级集合等线性集成预报更加准确。智协飞等（2020）采用LSTM对中国地区2 m气温进行多模式集成预报，试验表明LSTM显著提升了我国多数地区的气温预报水平，优于消除偏差集合平均和超级集合预报。目前，基于机器学习的多模式集成技术研究较少。并且现有的方法主要是针对温度等连续变量的确定性集成预报，对降水、风等非连续变量以及概率预报方面需要进一步研究。

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Research Progress of Multimodel Ensembe Forecast of Surface Meteorological Elements

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Abstract: Nowadays, ensemble forecasting has become the main support for operational weather forecasting. However, due to the limitations and imperfections of the numerical model itself, and the ensemble forecast system constrained by initial perturbation schemes, ensemble size, etc., the forecast results are generally biased. In addition, different forecasting models usually have different physical parameterization schemes, initial conditions, etc., resulting in different forecasting capabilities. Therefore, how to eliminate biases and how to make full and effective use of forecast information from different models to obtain more accurate weather forecasts has received extensive attention. In recent years, using statistical theory and forecasting diagnosis, multimodel ensemble forecasting technologies based on multiple ensemble prediction systems have been rapidly developed to effectively eliminate systematic biases and improve weather forecasting skills. For the three most basic surface meteorological variables (i.e., temperature, precipitation, wind), the widely used multimodel ensemble technologies such as ensemble mean (EM), bias-removed ensemble mean (BREM), superensemble (SUP), Bayesian model averaging(BMA), and ensemble model output statistics(EMOS) are first introduced from the perspective of deterministic forecasting and probabilistic forecasting. Finally, the issues that need to be paid attention to when using and developing multimodel ensemble technologies are discussed, including the consideration the number of participating models, the development of categorized precipitation and wind speed forecast models. Meanwhile, the combination of multimodel ensemble with machine learning deserves more investigation.

Key words: surface meteorological variables; multimodel ensemble forecasting; deterministic forecasting; probabilistic forecasting