School of Mathematical and Physical Sciences

University of Reading

The Search for Gaussian Moisture Variables at the Convective Scale

Hristo Chipilski | David Livings | Ross Bannister

Introduction

Moisture variables are characterised by non-Gaussian error distributions which make them hard to assimilate, especially at the convective scale. The current study examines two distinct approaches to alleviate this problem. The first one tests the suitability of physical moisture variables, while the second one introduces a novel statistical transformation to normalise the moisture error distributions.

Methodology

- Background moisture errors are calculated by taking the difference between 6h and 3h forecast fields valid at the same time (NMC method).
- Model data is taken from the United Kingdom Variable (UKV) model – the high-resolution version of the Met Office Unified Model (UM).

1. RH_{700} & PW
2. Moist and dry cases

1. Test symmetry assumption
2. Skewness profiles

1. Distribution plots
2. Probability plots

Physical variables

Original background errors are characterised by double exponential (Laplace) distributions.

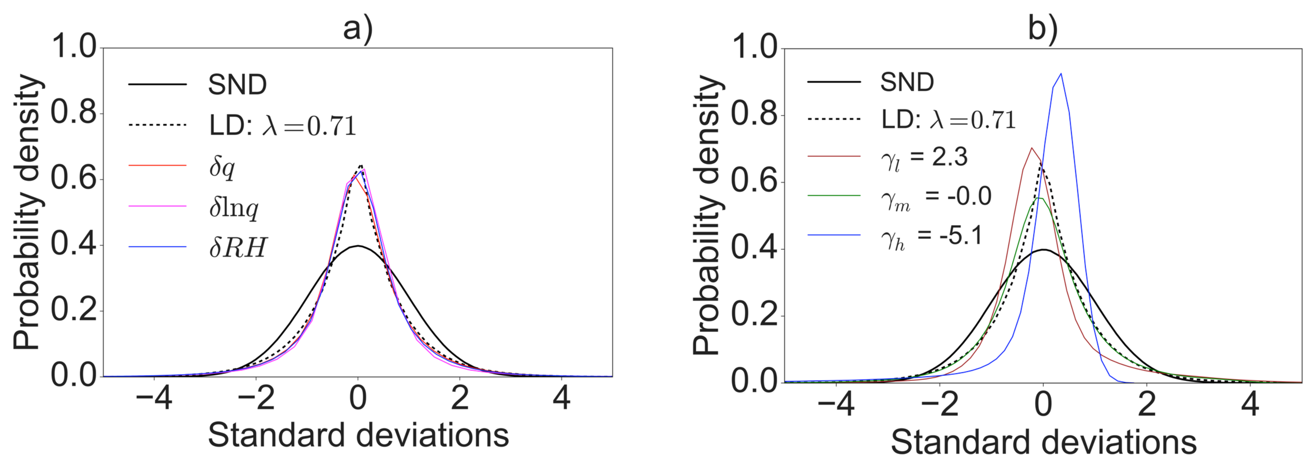


Figure 1. *a) Unconditioned moisture error distributions of q, lnq and RH; b) RH error distributions conditioned on the background 3h RH field.*

Hólm's tranform (Hólm, 2003)

$$\delta\varphi' = \frac{\delta\varphi - b_{\delta\varphi}(\Phi)}{\sigma_{\delta\varphi}(\Phi)}$$

δφ : moisture analysis increment
Φ : stratifying variable
σ,b : standard deviation and bias

What is the best choice of **δφ** and **Φ**?

Bulk Distribution Analysis

The best BDA candidates are determined according to mean absolute skewness.

Table 1. *Vertical mean absolute skewness for all cases.*

	w	T	p	q	av
δq	0.7	0.6	0.5	1.3	0.5
δlnq	4.0	2.5	2.7	3.7	3.1
δRH	1.8	1.3	1.1	3.0	0.8

Detailed Distribution Analysis

- Deviations from Gaussianity still present.

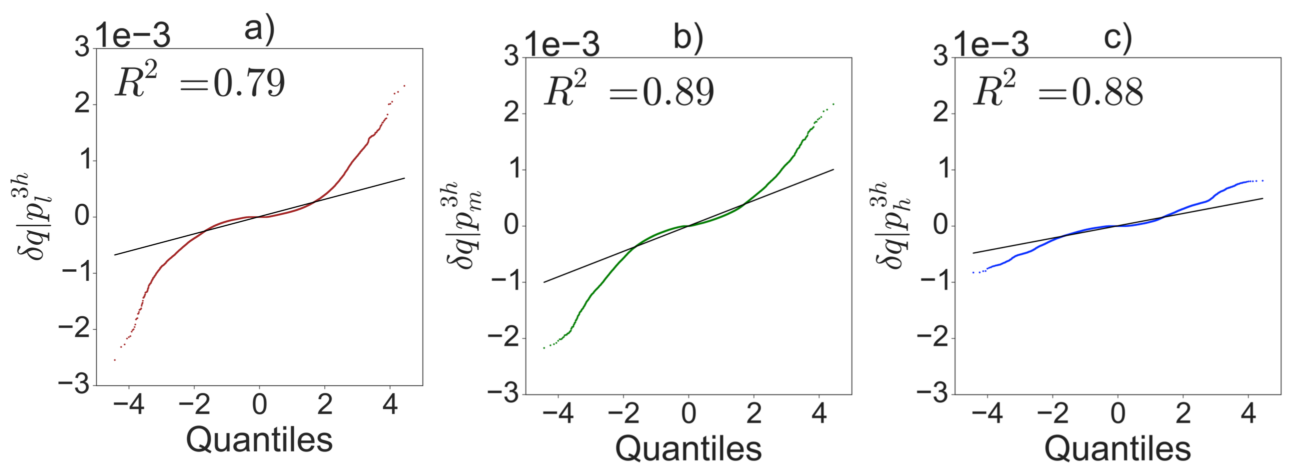


Figure 2. *Normal probability plots for* $\delta q|p^{3h}$.

- Similar performance to nonlinear version of Hólm's transform.

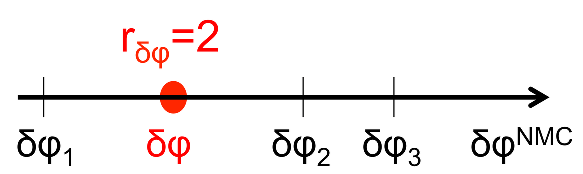
Statistical variables

Rank-Based Inverse Normal Transform (RBINT)

$$\delta\varphi' = G^{-1}\left(\frac{r_{\delta\varphi} - c}{N - 2c + 1}\right)$$

G : normal CDF **$r_{\delta\varphi}$** : relative rank
N : sample size **c** : constant offset
(Beasley and Erickson, 2009)

- RBINT requires:
a) NMC climatology;
b) Definition for $\mathbf{r_{\delta\varphi}}$.



Effect of RBINT on the spatial structure of moisture errors

Small errors are *inflated*, whereas **large errors** are *compressed*.

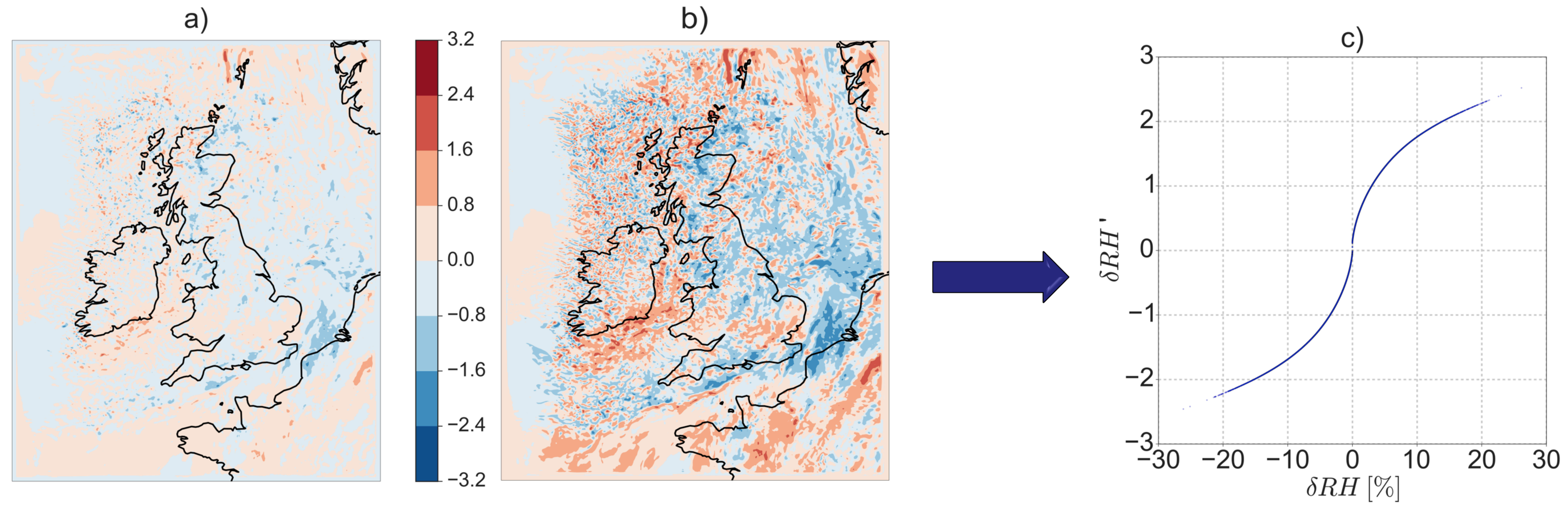


Figure 3. *Original (a) and RBINT (b) relative humidity errors for 15/09/2013. Relationship between original and RBINT space is shown in (c).*

RBINT performance according to BDA-DDA procedure

- RBINT is symmetric for all UKV model levels.
- Gaussian fit of RBINT moisture errors is superior to original moisture errors.

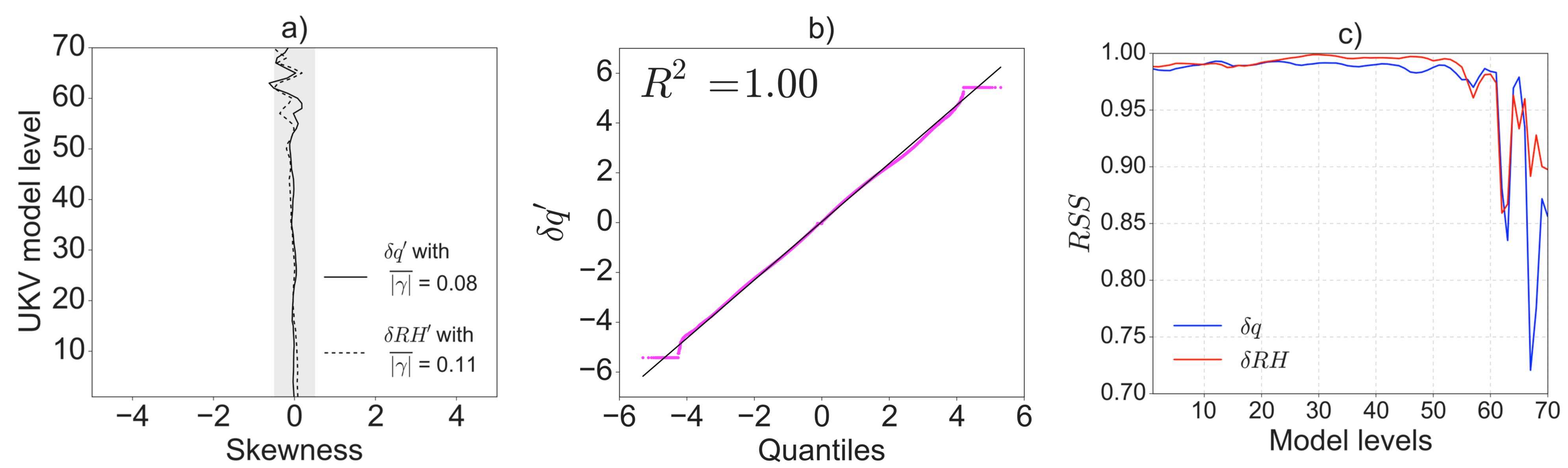


Figure 4. *a) Vertical skewness profile; b) normal probability plot of δq (no linear interpolation) for the testing data set and model level 20; c) relative skill score (RSS).*

Conclusions

- Physical variables used in global data assimilation are not suitable for convective scale moisture data assimilation.
- RBINT successfully normalises the background moisture error distributions for both training and testing data sets.
- RBINT can be implemented in operational VAR data assimilation system.

References

1. Beasley, T. M., and S. Erickson, 2009: Rank-Based Inverse Normal Transformations are increasingly used, but are they merited? Behav. Genet., 39 (5), 580–595.
2. Hólm, E., 2003: Revision of the ECMWF humidity analysis: construction of a gaussian control variable. ECMWF/GEWEX Workshop on Humidity Analysis, 8-11 July 2002, ECMWF, Shinfield Park, Reading, 36-43.