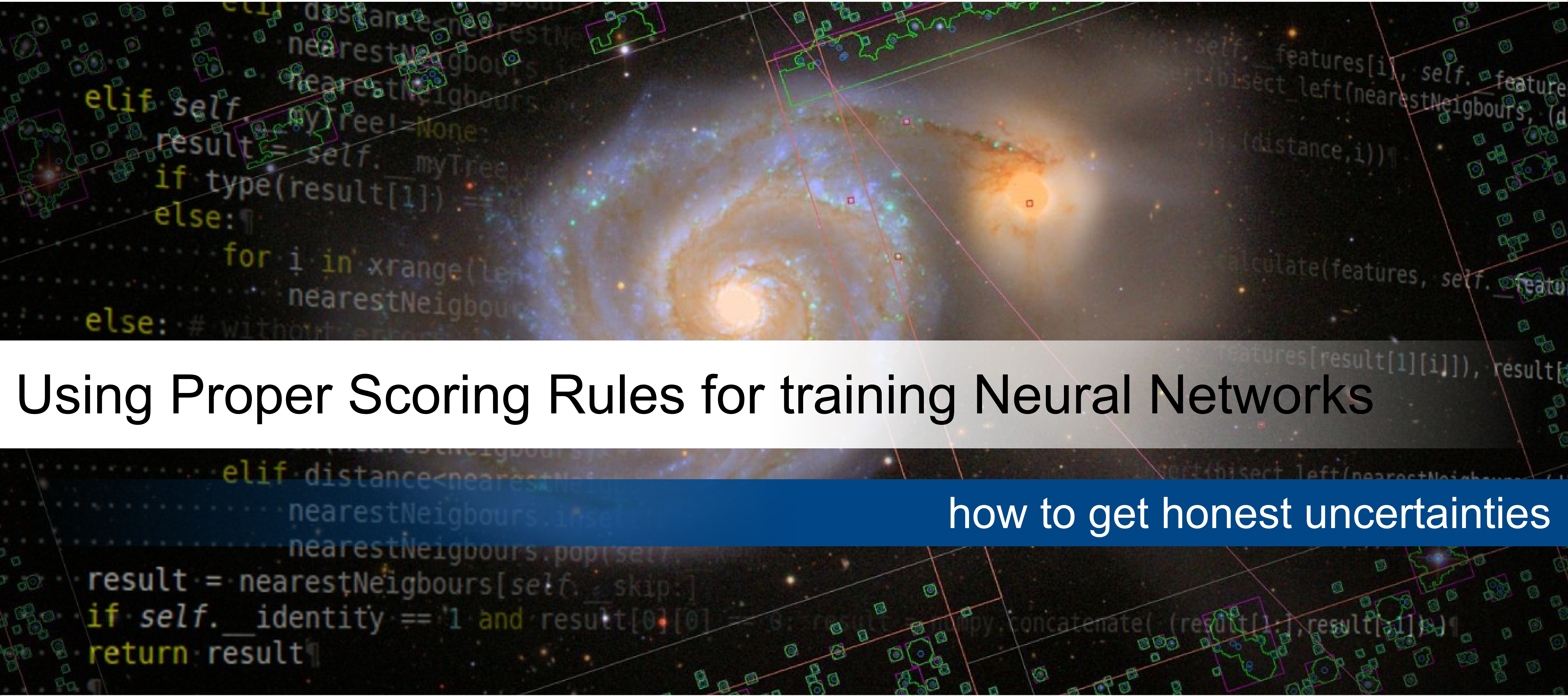


Using Proper Scoring Rules for training Neural Networks

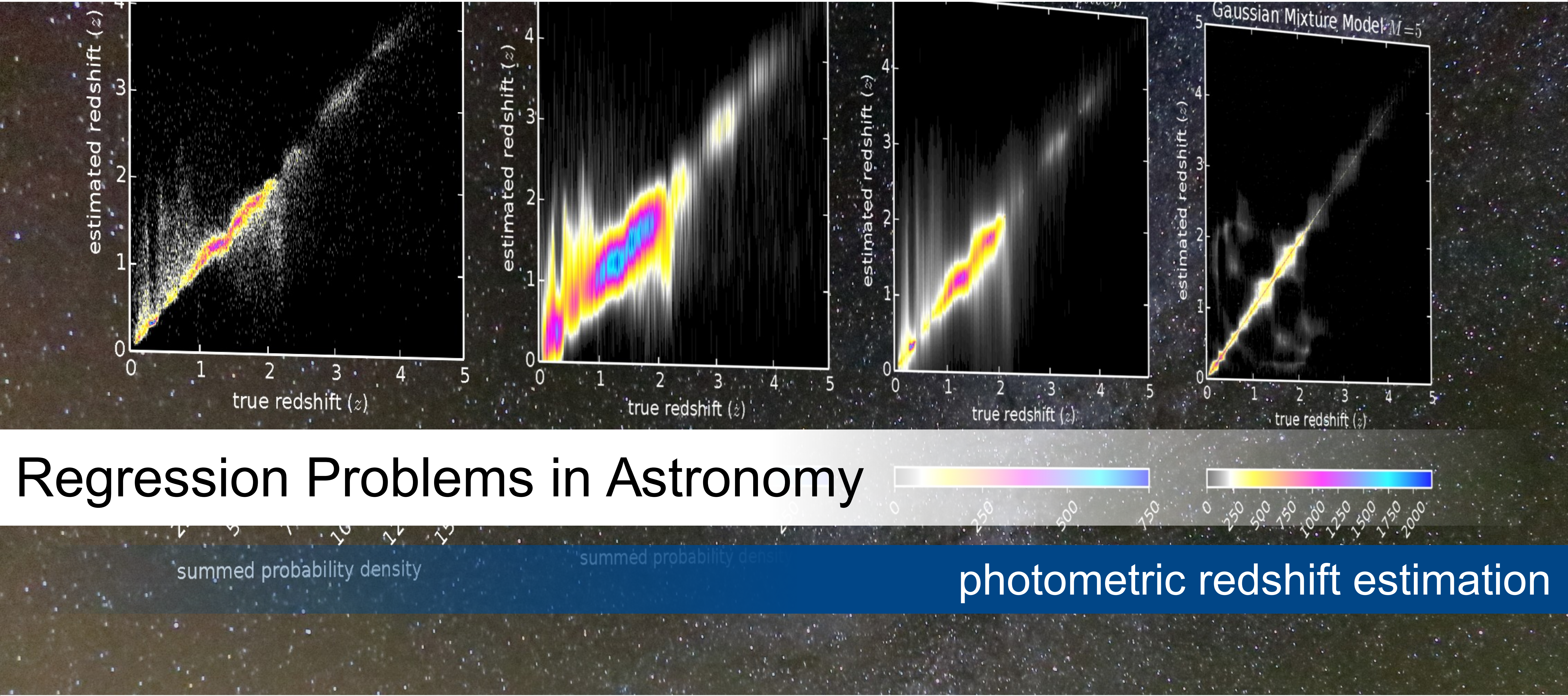
how to get honest uncertainties

model

estimate

$$f(\vec{x}) \rightarrow y, \text{where } \vec{x} \in \mathbb{R}^n, y \in \mathbb{R}$$

features

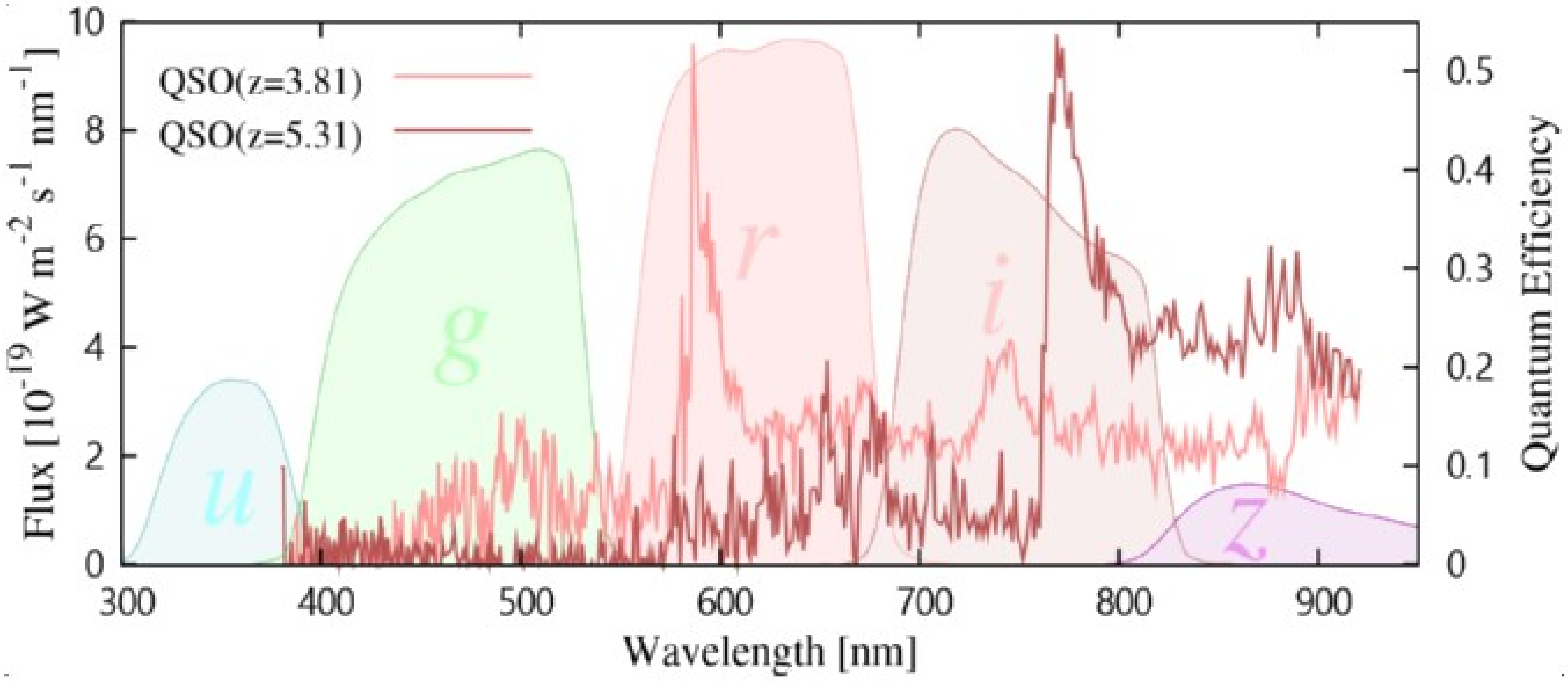


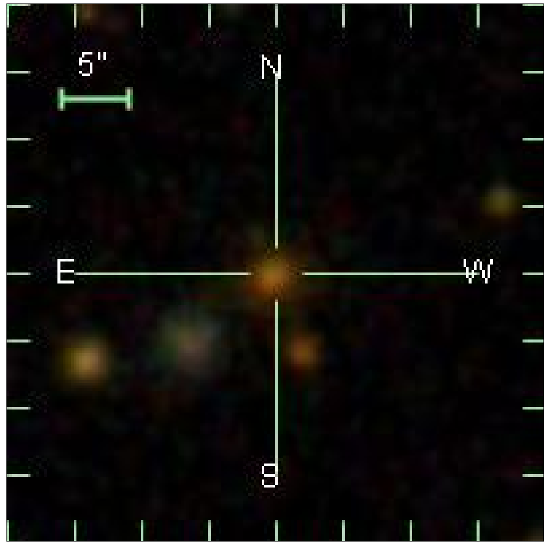
Regression Problems in Astronomy

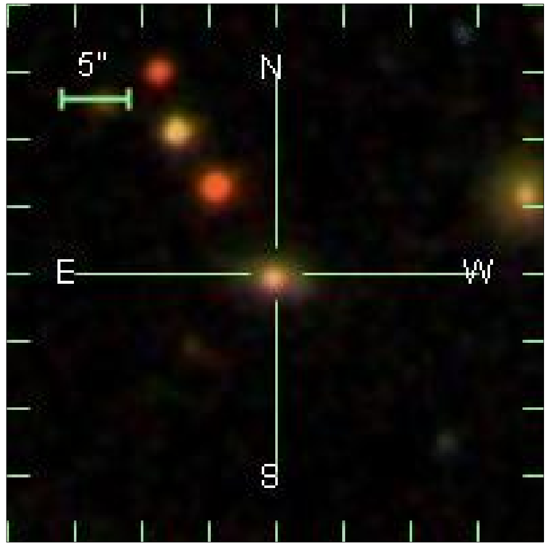
photometric redshift estimation

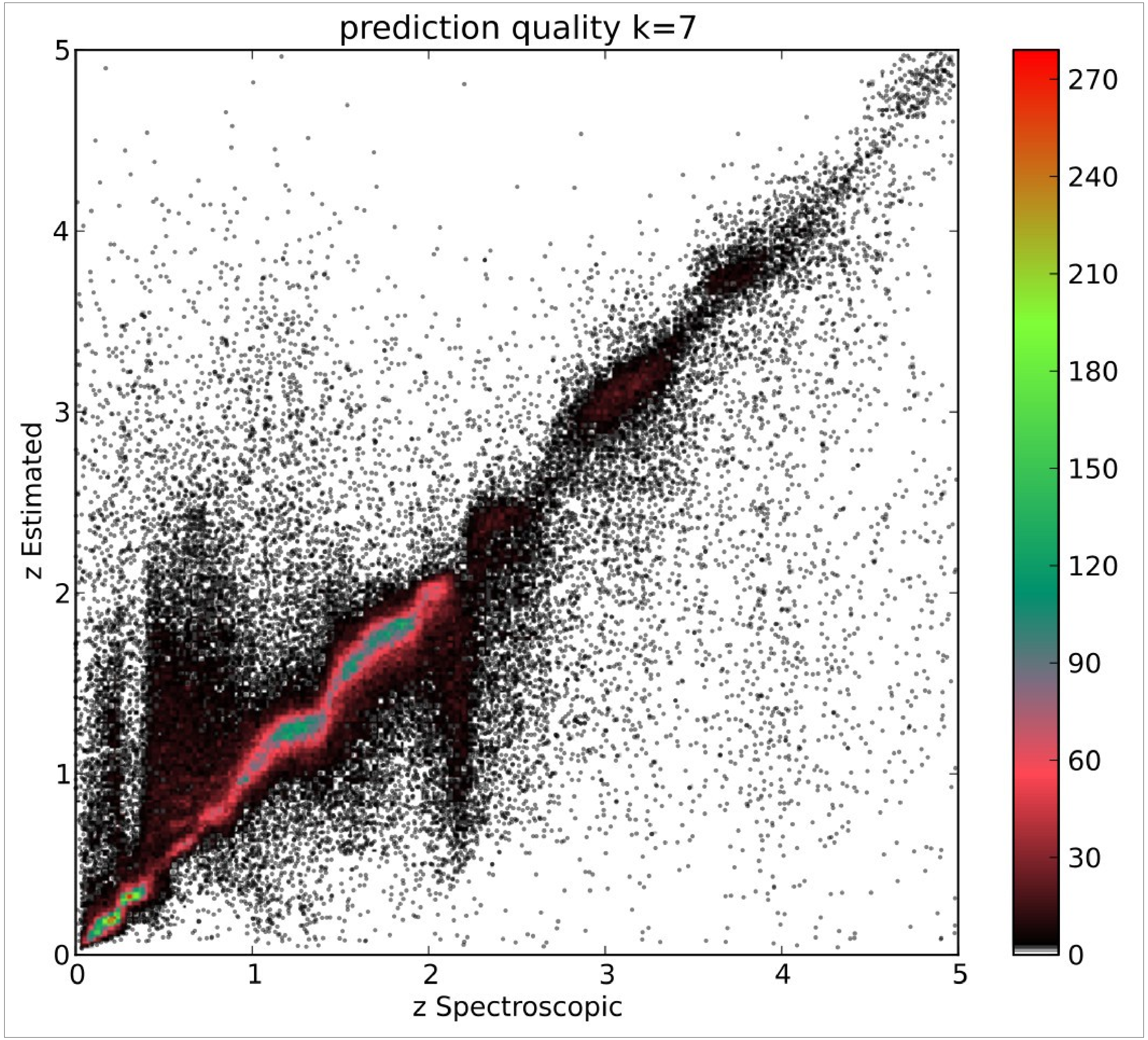
Estimating Redshift Photometrically

$$\boxed{1 + z = \frac{\lambda}{\lambda_0}}$$









Experiment with all quasars in SDSS DR7

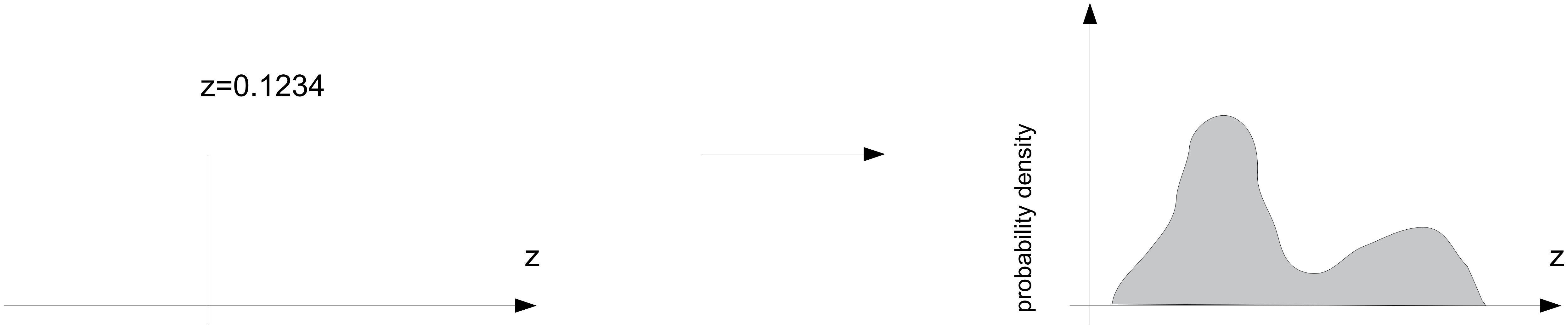
Uncertainties

$$f(\vec{x}) \rightarrow y\,,\, where\ \vec{x} \in \mathbb{R}^n\,,\, y \in \mathbb{R}$$

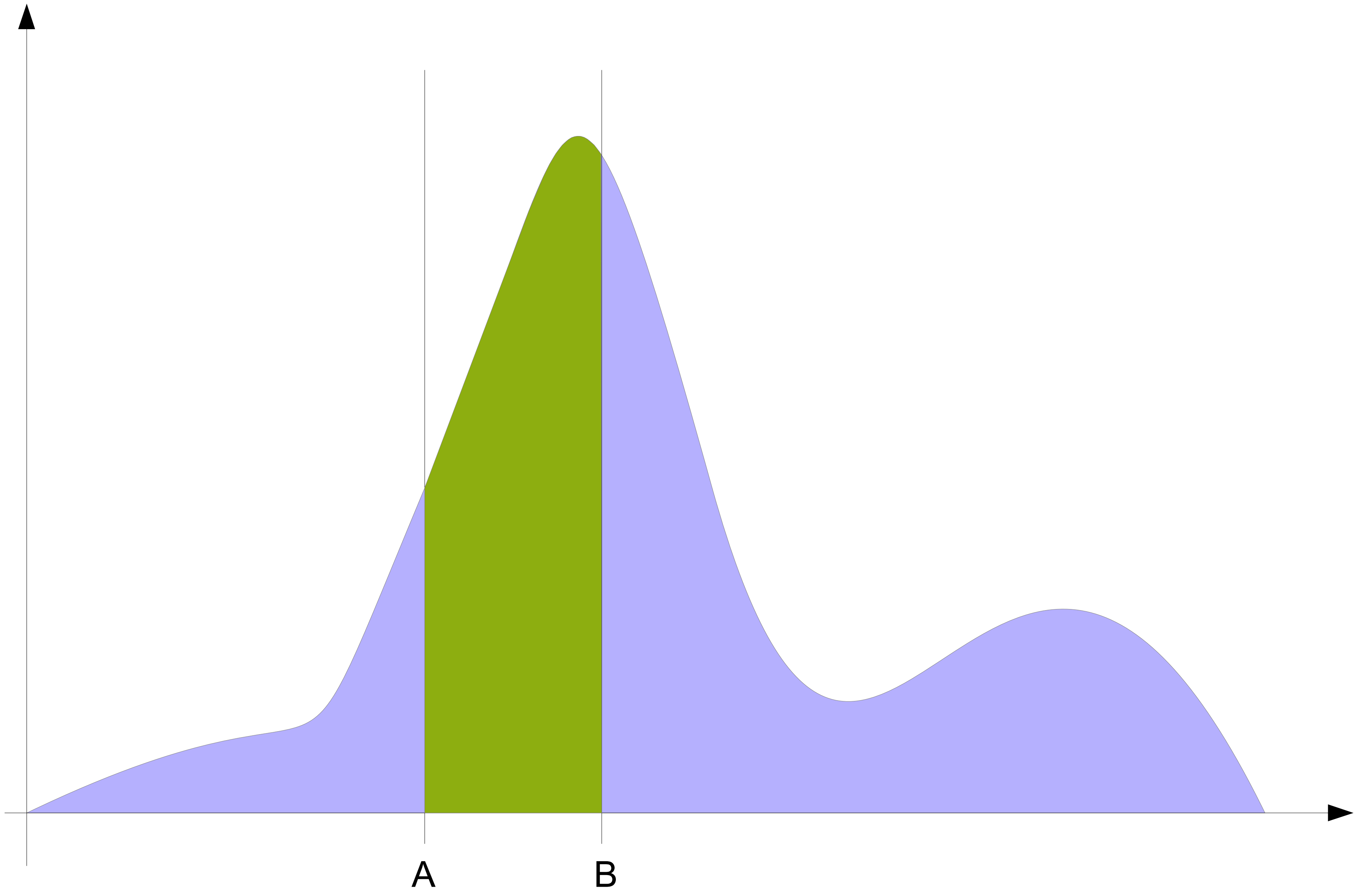
model uncertainty

input uncertainty

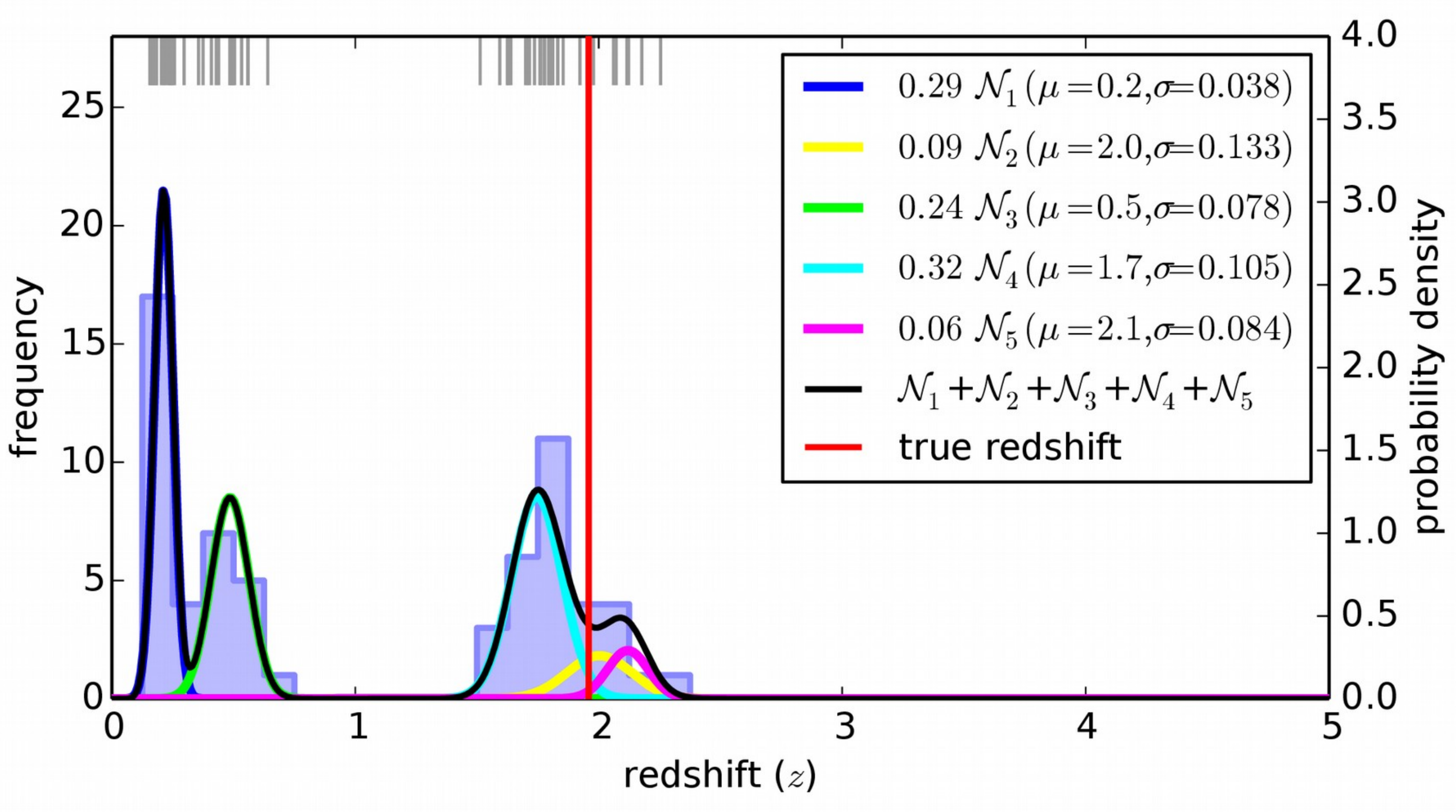
uncertain estimate



Probability Density Function



Multi-Modalities

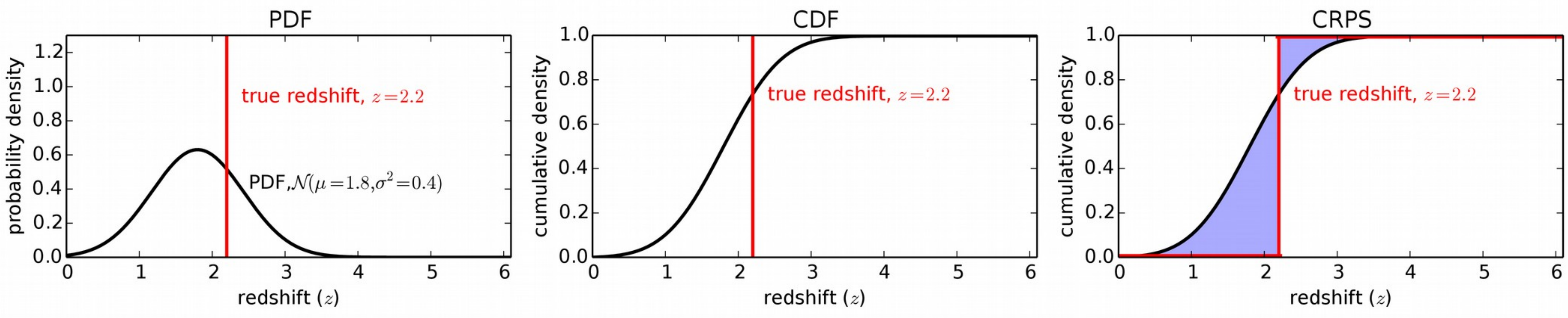


Proper Evaluation Tools / CRPS

continuous rank probability score

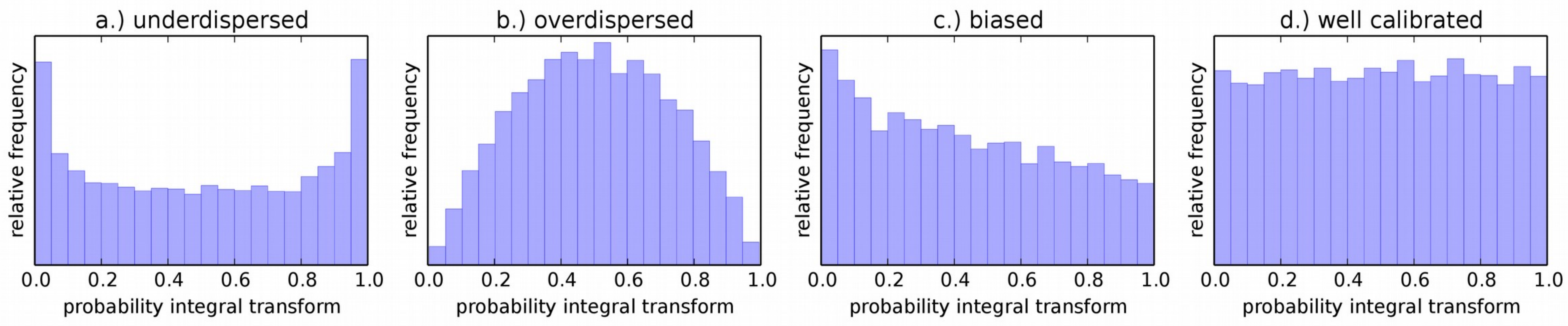
$$CRPS = \frac{1}{N}\sum_{t=1}^{N} crps(CDF_t, z_t),$$

$$\text{with } crps(CDF_t, z_t) = \int_{-\infty}^{+\infty} \left[CDF_t(z) - CDF_{z_t}(z)\right]^2 dz$$

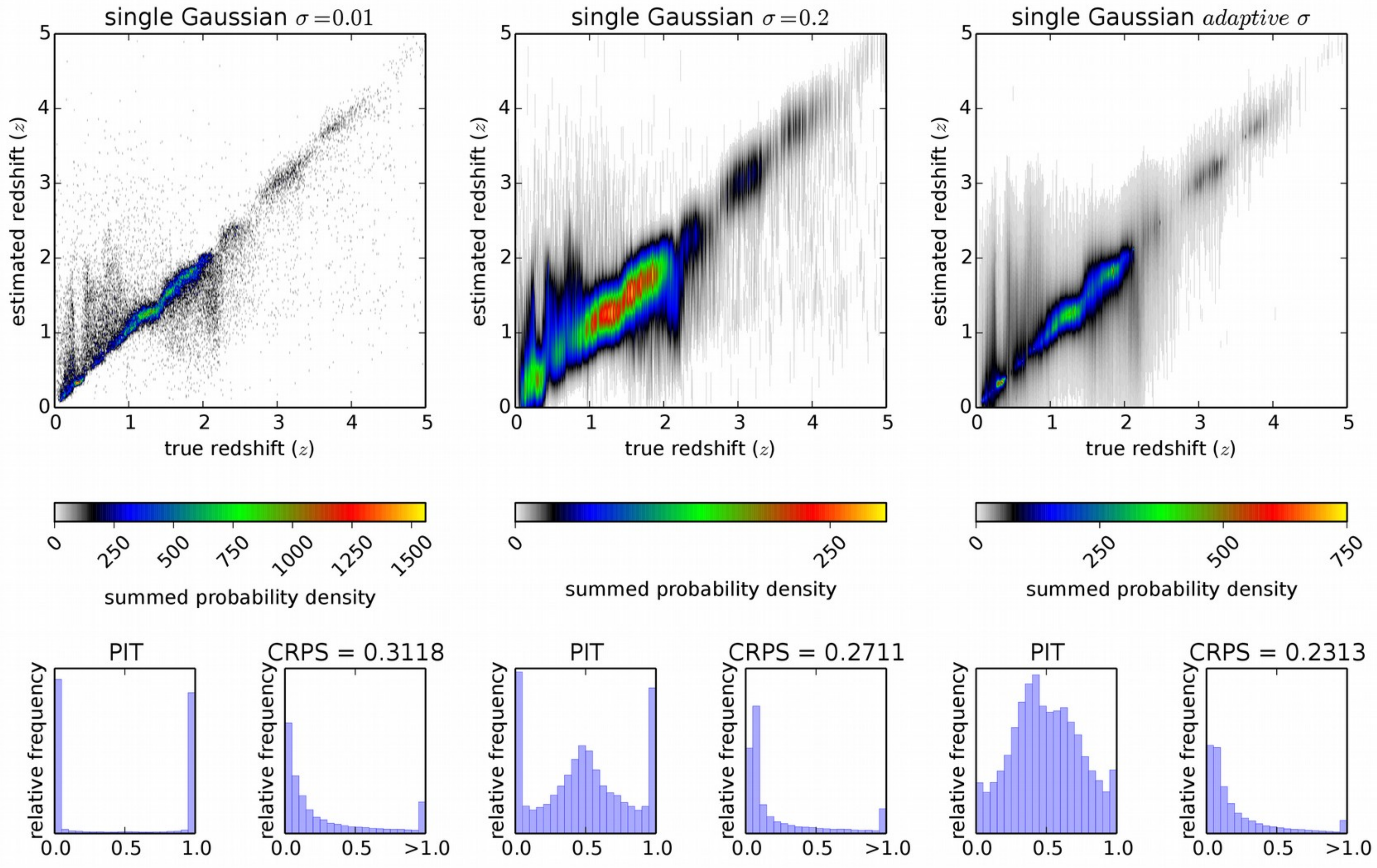


Proper Evaluation Tools / PIT

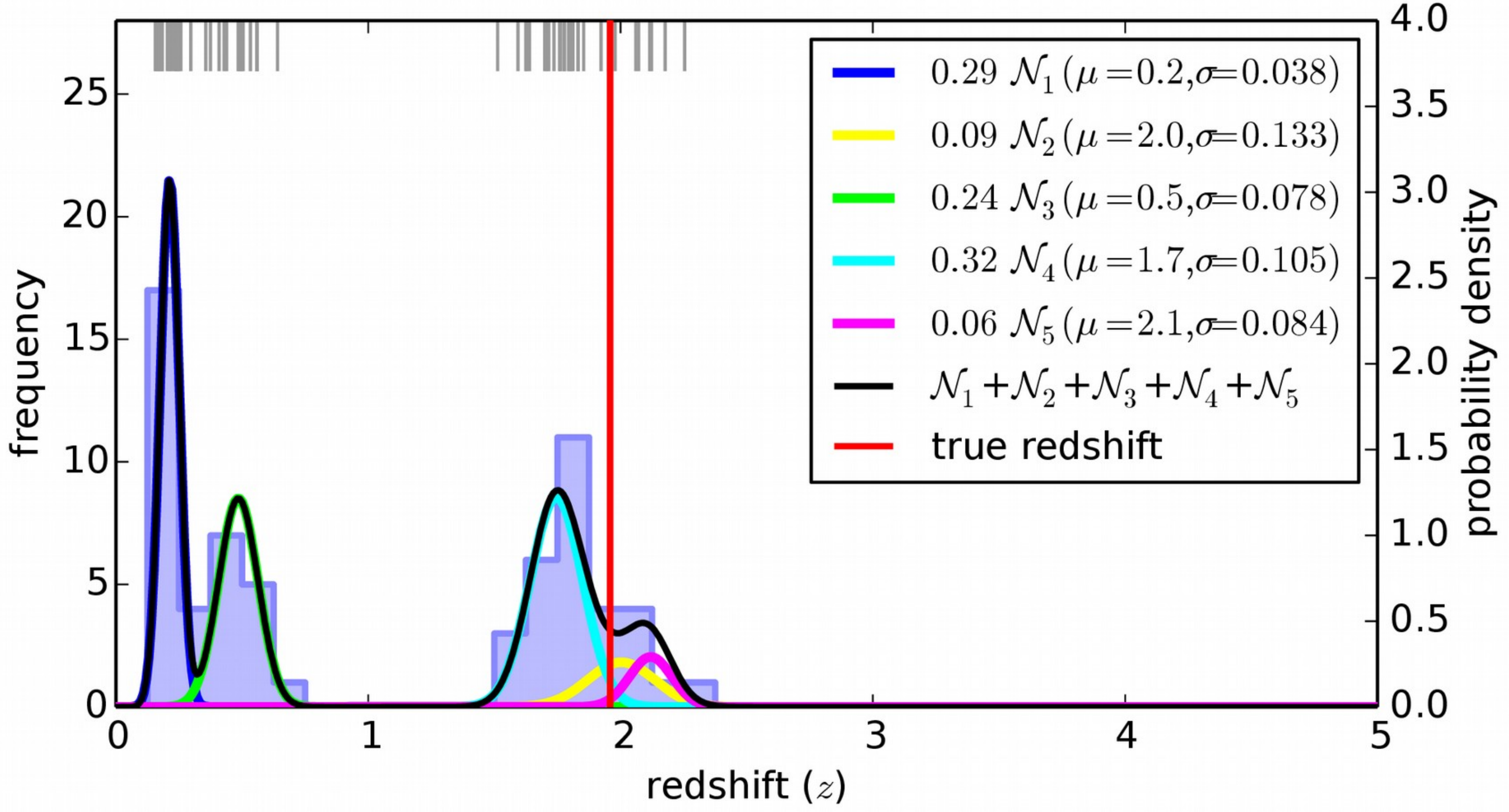
probability integral transform



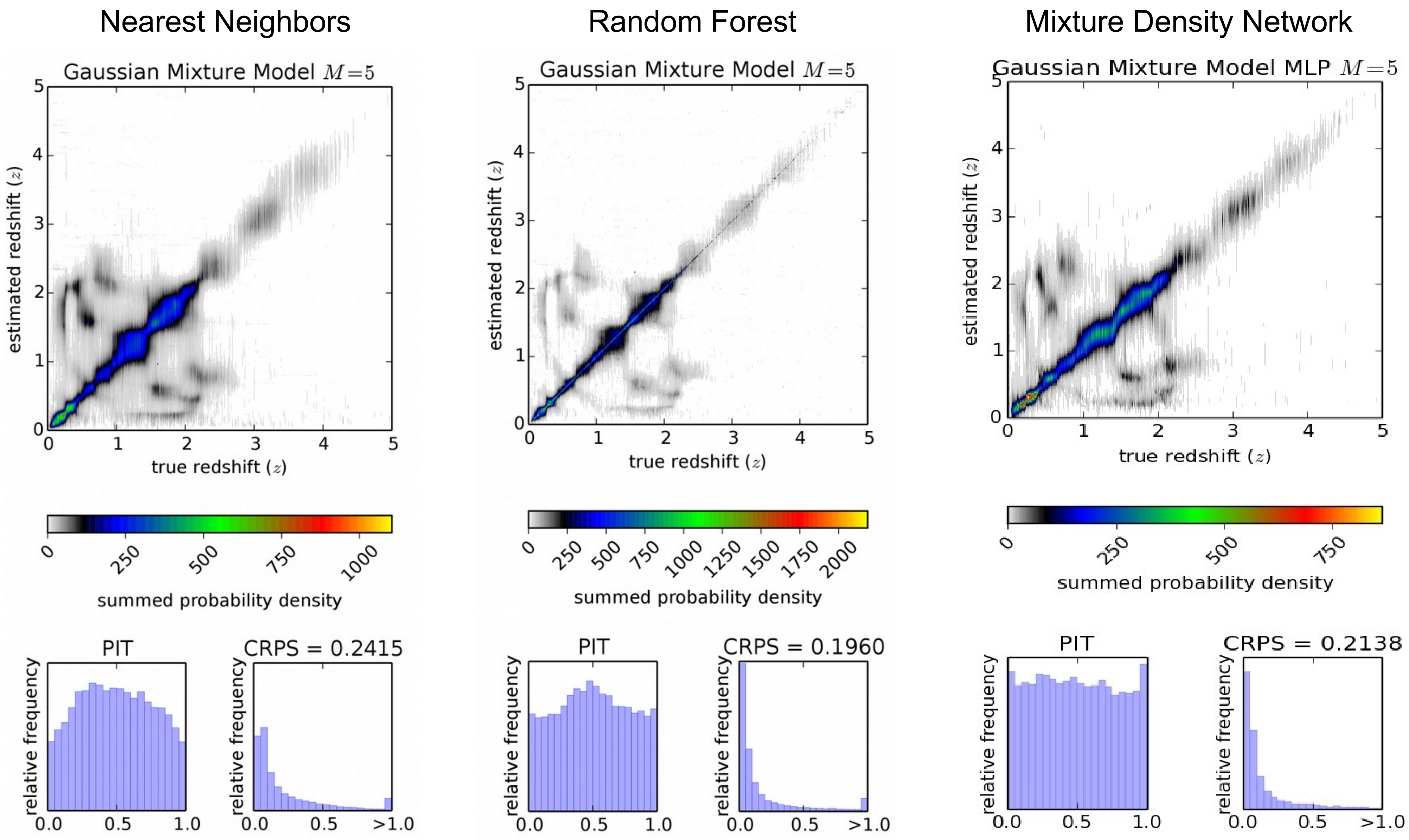
Uncertain Results / kNN



Multi-Modalities

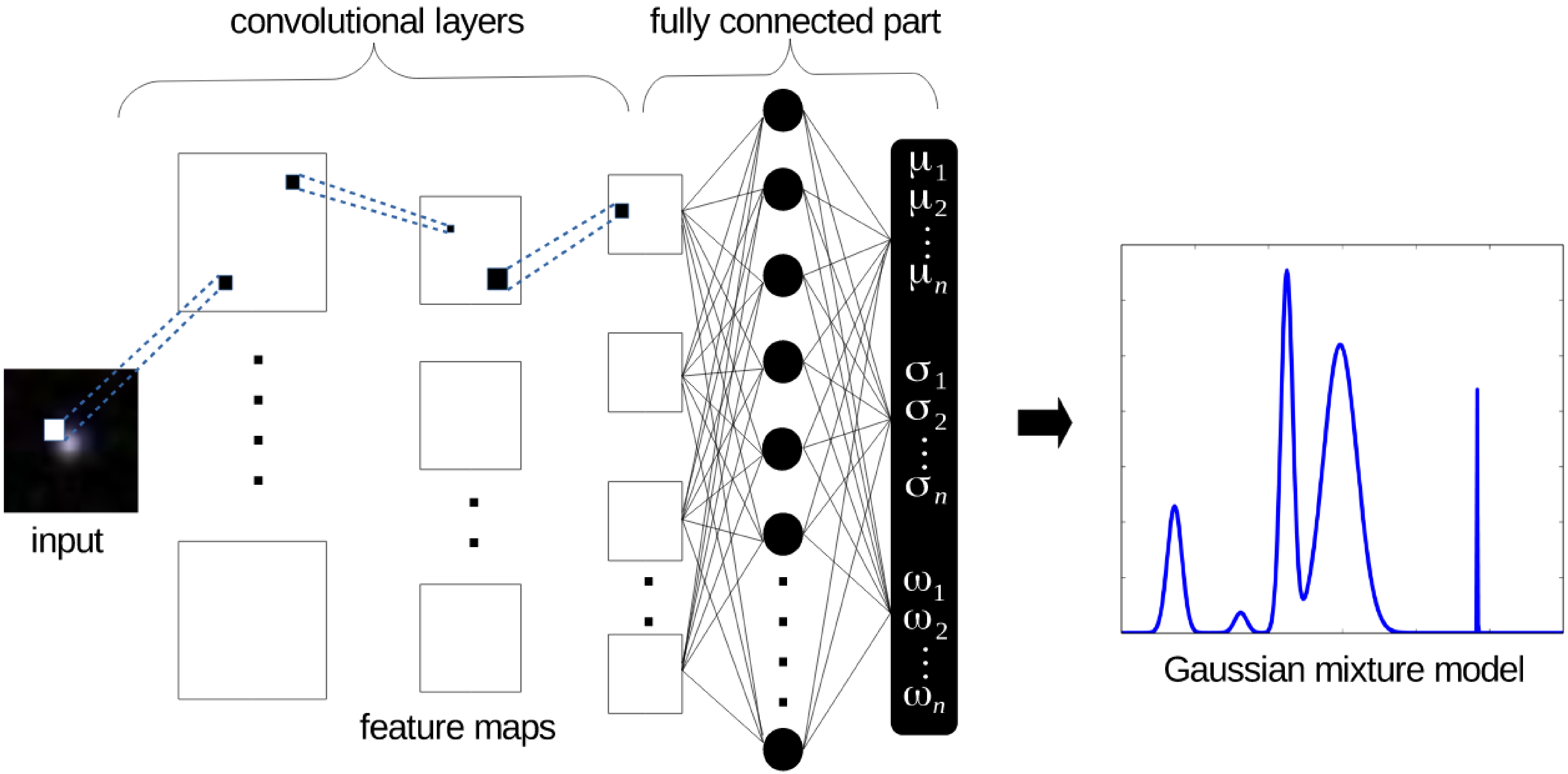


Results

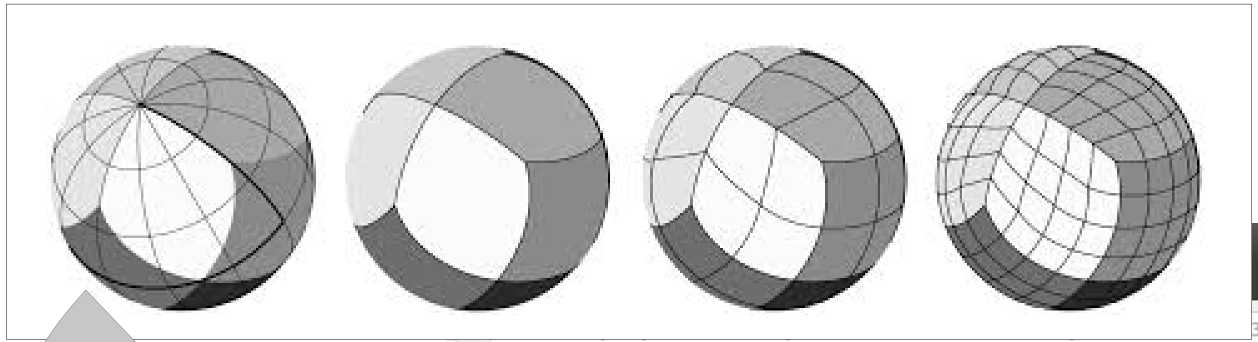


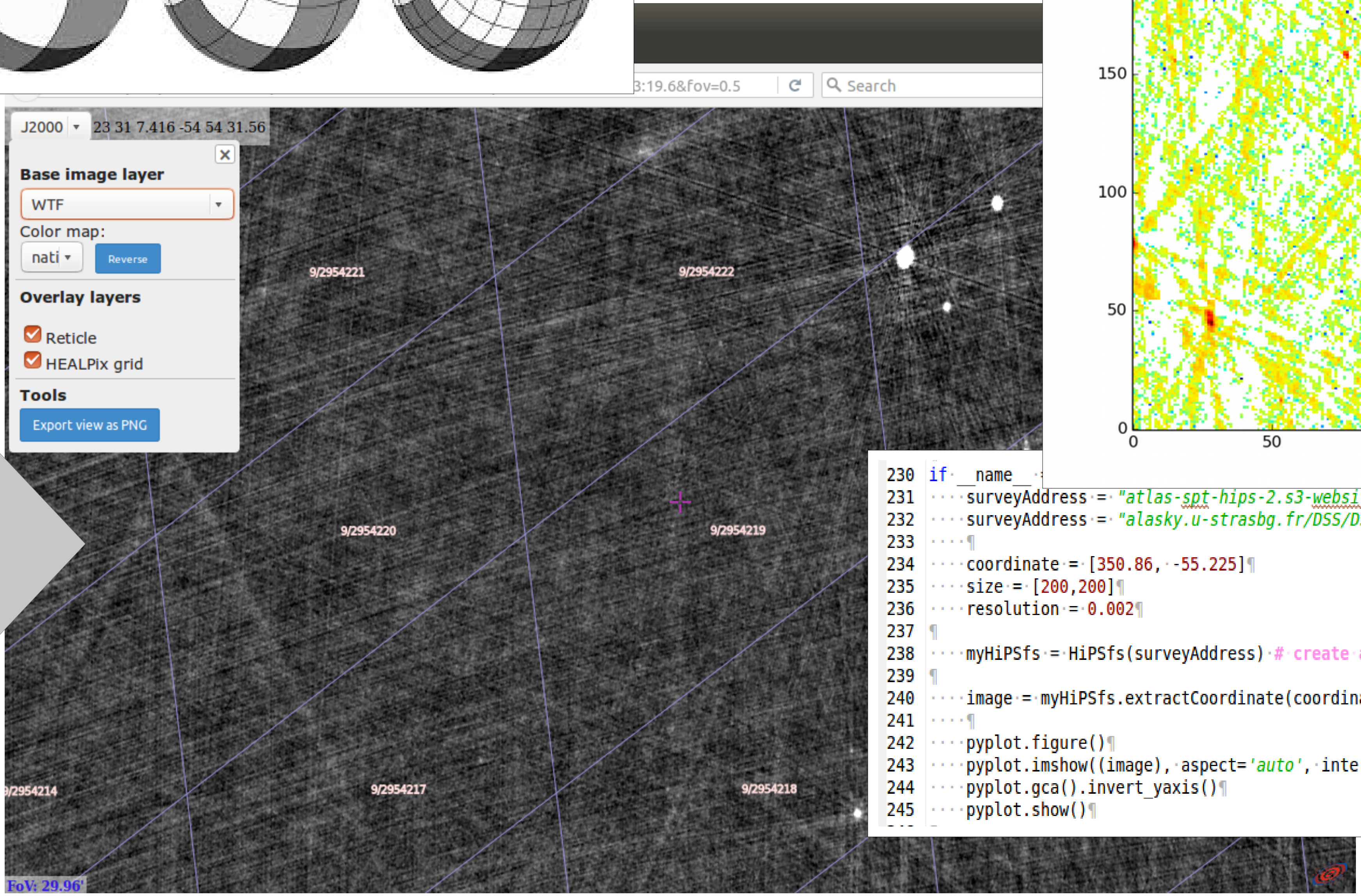
Nearest Neighbors
Random Forest
Mixture Density Network
Gaussian Mixture Model $M=5$
Gaussian Mixture Model $M=5$
Gaussian Mixture Model MLP $M=5$
estimated redshift (z)
true redshift (z)
summed probability density
0 250 500 750 1000
0 250 500 750 1000 1250 1500 1750 2000
0 250 500 750
PIT
CRPS = 0.2415
CRPS = 0.1960
CRPS = 0.2138
relative frequency
0.0 0.5 1.0
0.0 0.5 >1.0

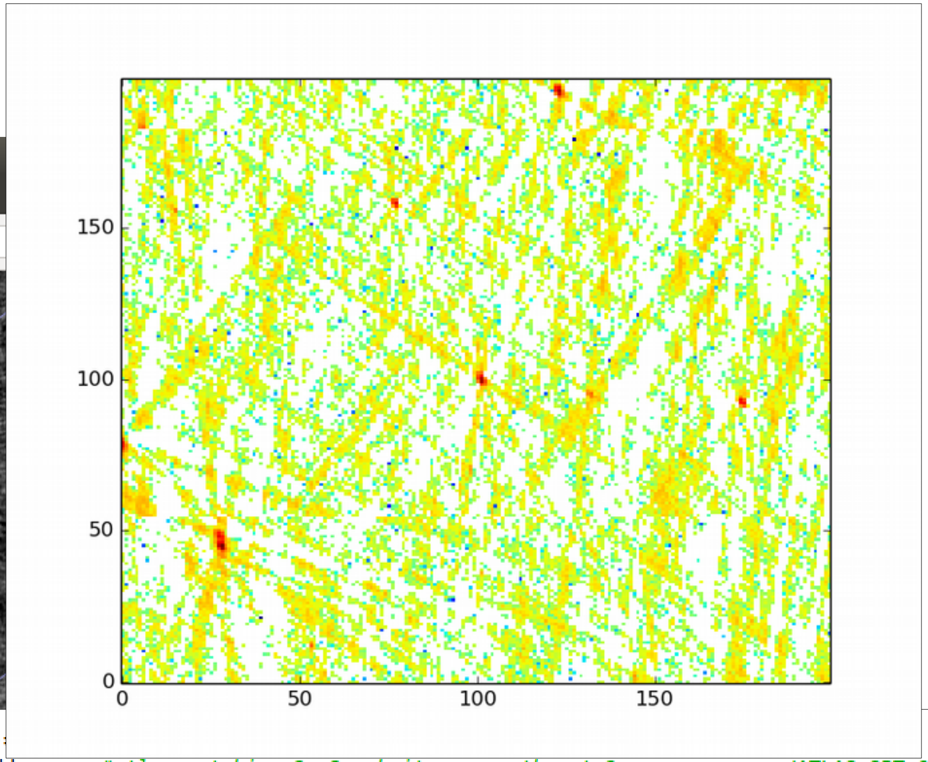
DCN meet MDN


convolutional layers
fully connected part
input
feature maps
μ_1
μ_2
μ_n
σ_1
σ_2
σ_n
ω_1
ω_2
ω_n
Gaussian mixture model

Healpix / HiPS / IVOA

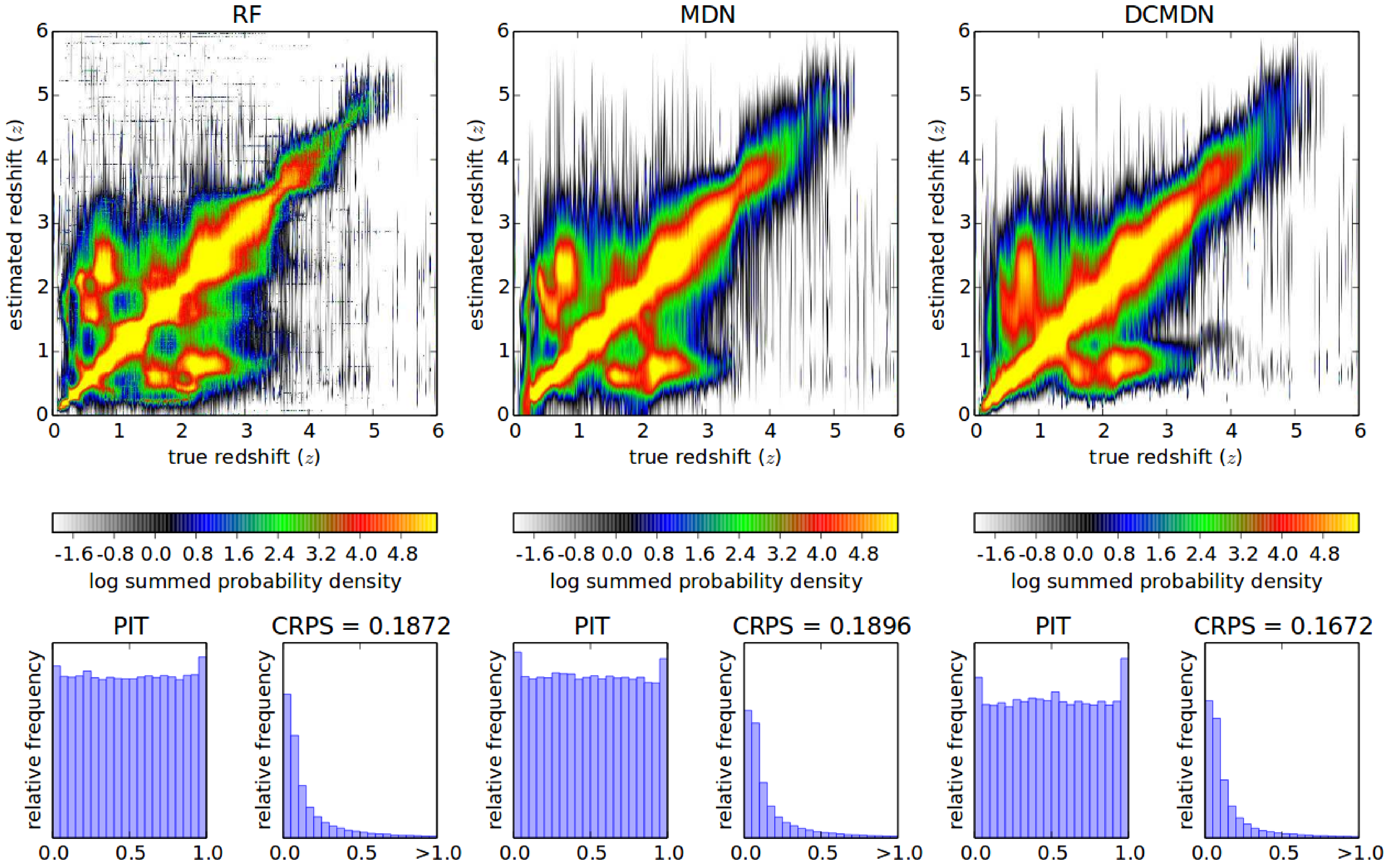






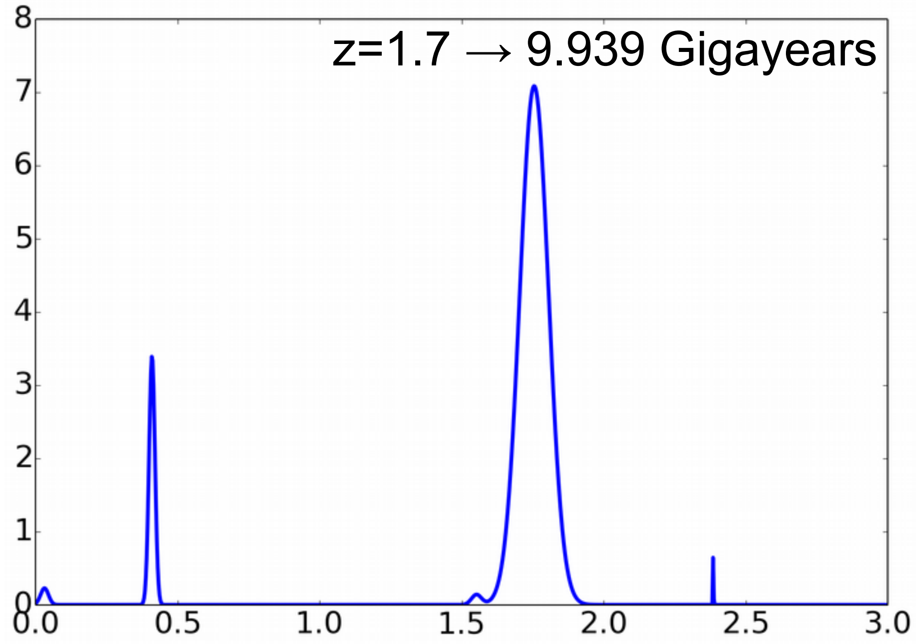

```python
if __name__
    surveyAddress = "atlas-spt-hips-2.s3-website-ap-southeast-2.amazonaws.com/ATLAS-SPT-64x64"
    surveyAddress = "alasky.u-strasbg.fr/DSS/DSS2Merged" # DSS red

    coordinate = [350.86, -55.225]
    size = [200,200]
    resolution = 0.002

    myHiPSfs = HiPSfs(surveyAddress) # create access

    image = myHiPSfs.extractCoordinate(coordinate, size, resolution, nested=True) # extract data array

    pyplot.figure()
    pyplot.imshow((image), aspect='auto', interpolation="nearest")
    pyplot.gca().invert_yaxis()
    pyplot.show()
```

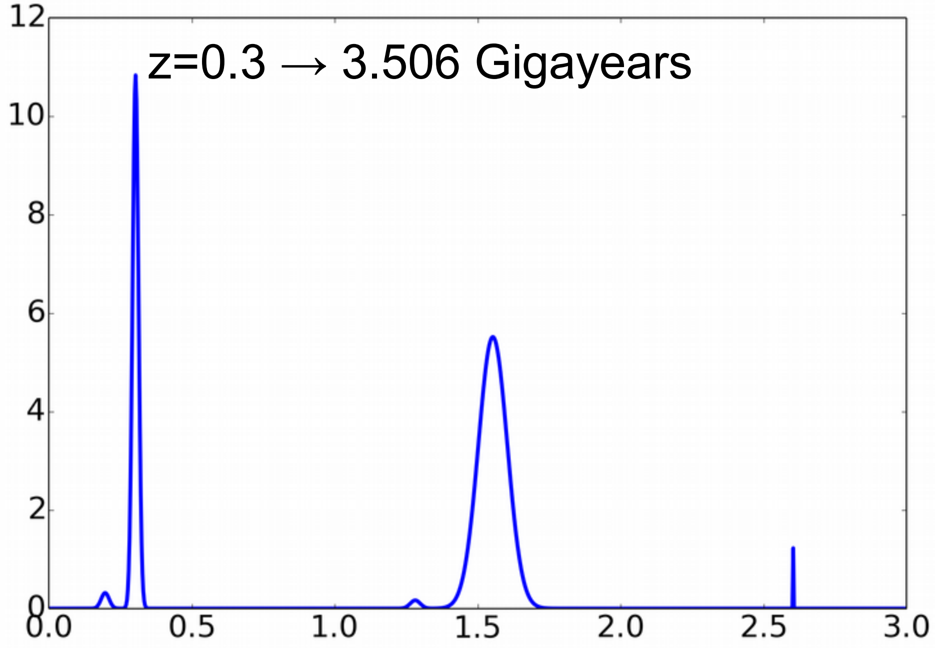
Results



D'Isanto 2018

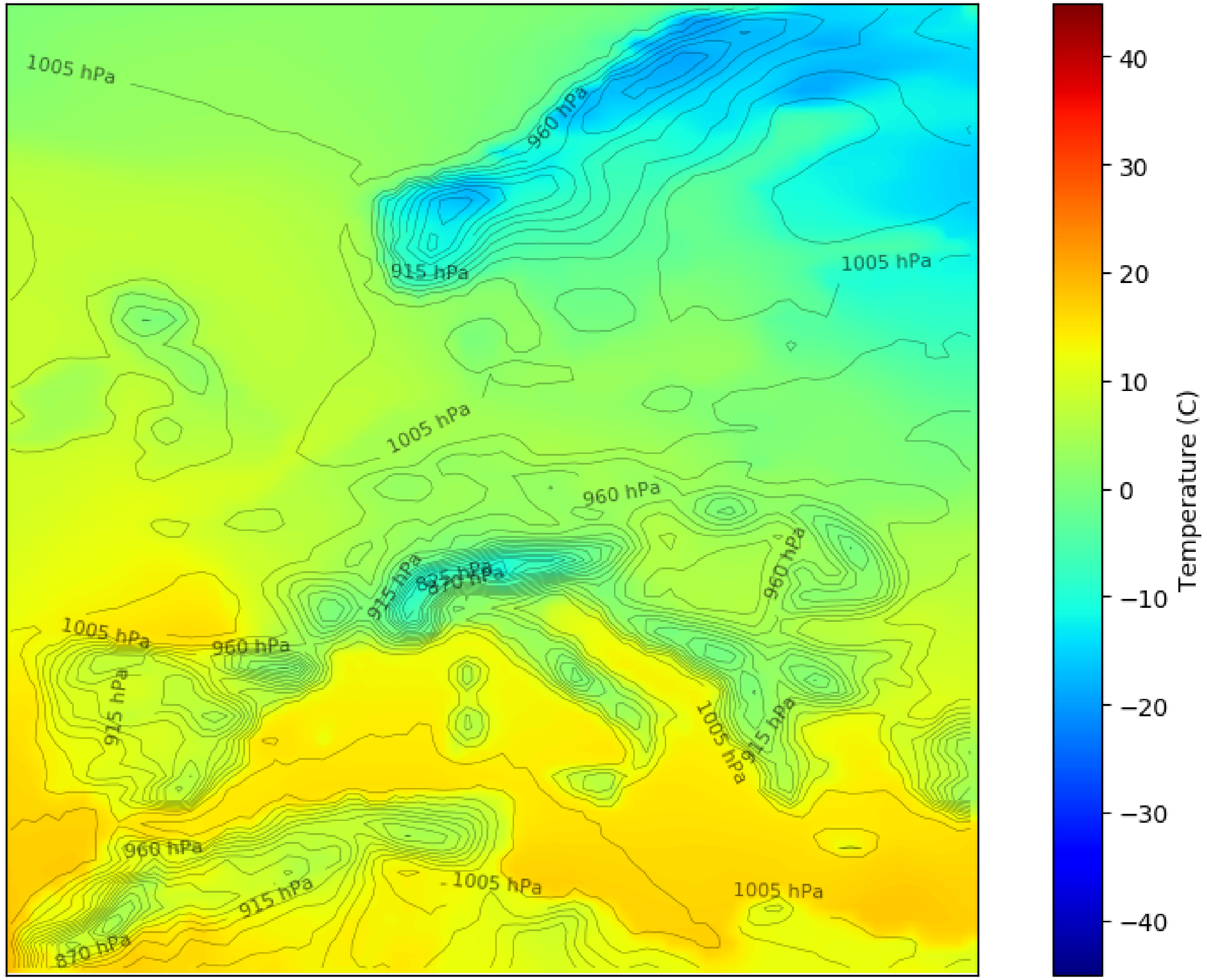
Challenges / Limitations

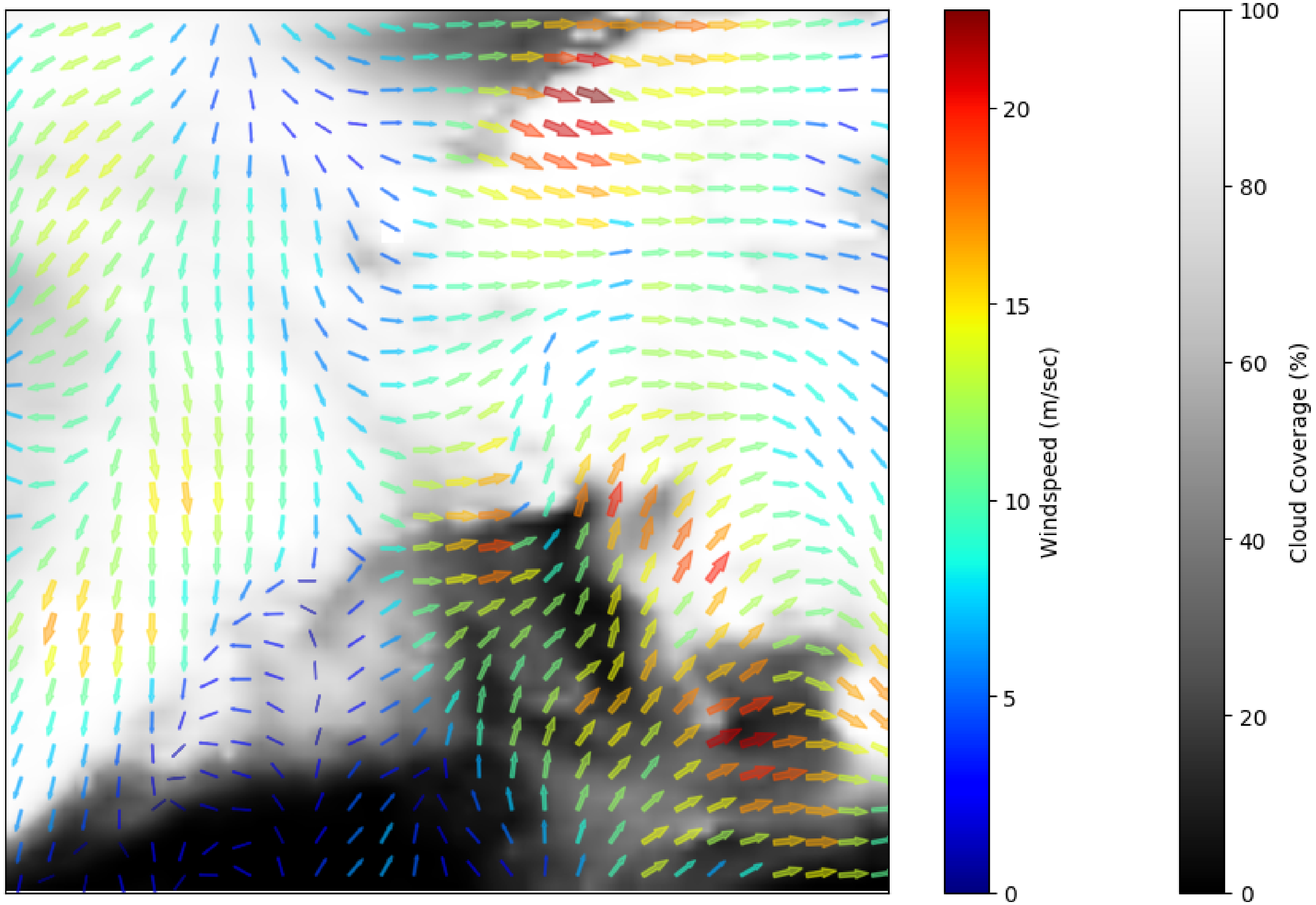




Weather Forecast Simulations

European Centre for Medium-Range Weather Forecasts (ECMWF)

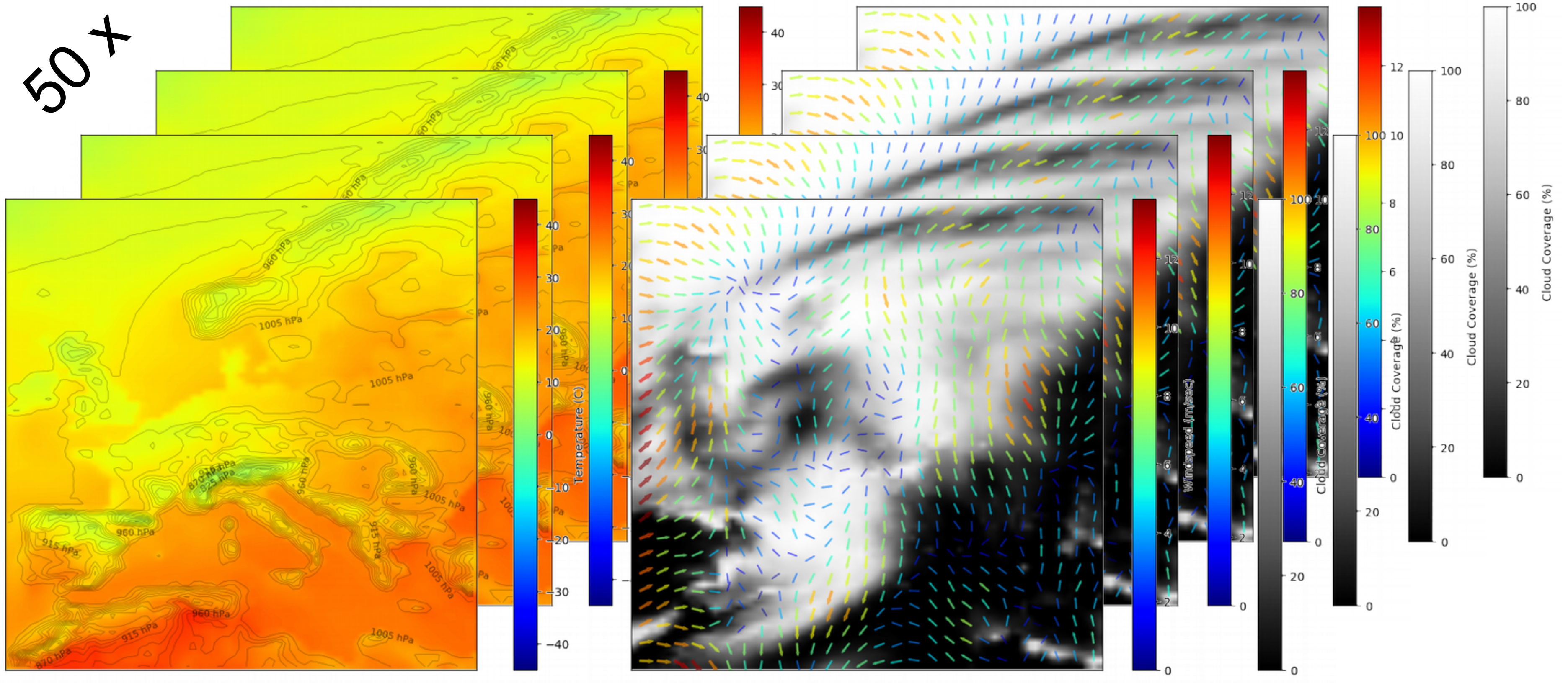




Weather Forecast Simulations

In this example 18 parameters on 81x81 grid for Europe (0.5°, 0.5°)

- t2m: air temperature 2m above ground
- cape: convective available potential energy
- sp: surface pressure
- tcc: total cloud cover
- sshf: sensible heat flux
- slhf: latent heat flux
- u10: 10-meter U-wind
- v10: 10-meter V-wind
- d2m: 2-meter dew point temperature
- ssr: short wave radiation flux
- str: long wave radiation flux
- sm: soil moisture
- u pl500: u-wind at 500 hPa
- v pl500: v-wind at 500 hPa
- u pl850: u-wind at 850 hPa
- v pl850: v-wind at 850 hPa
- gh pl500: Geopotential at 500 hPa
- q pl850: specific humidity at 850 hPa

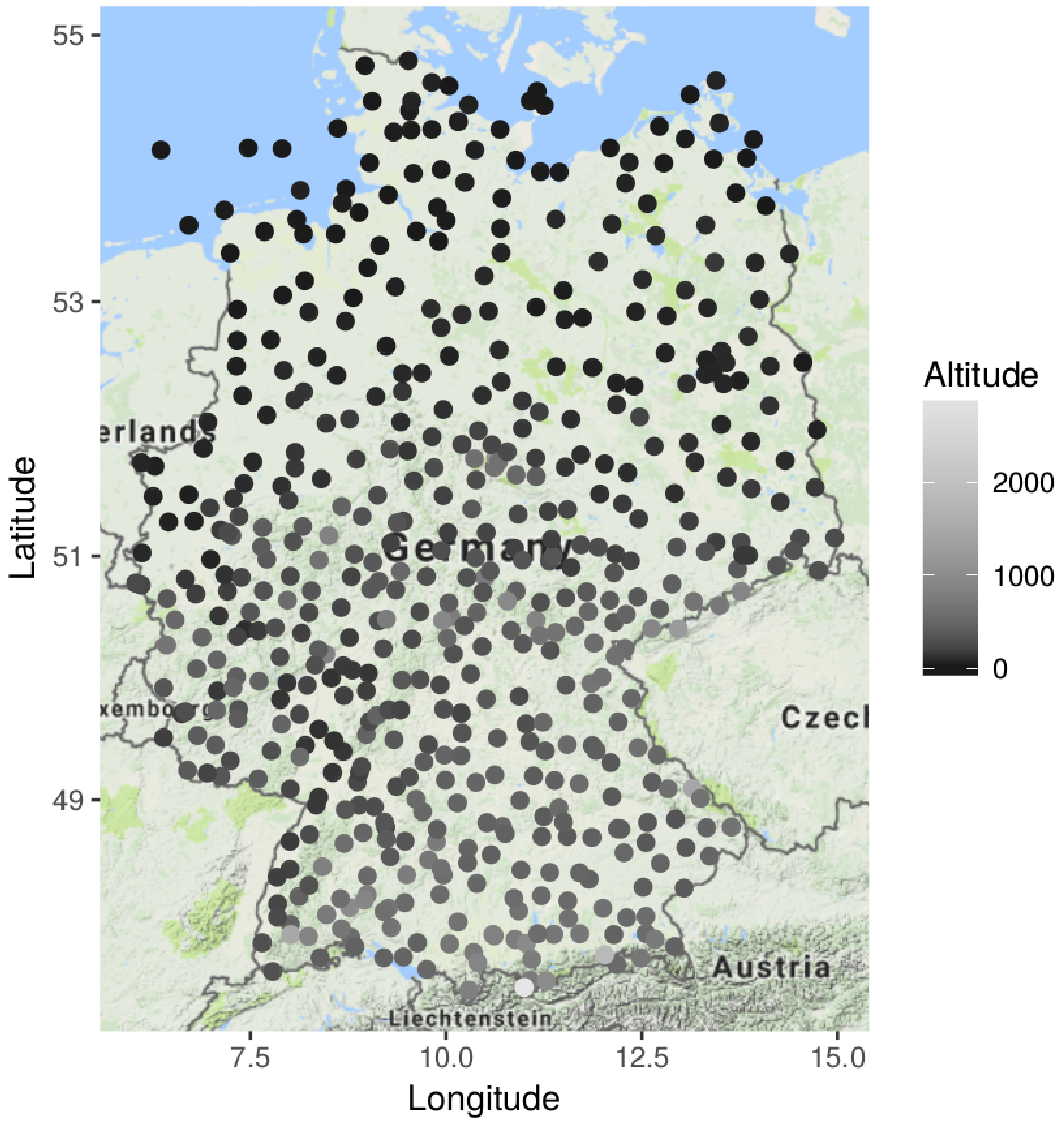


Statistical Post-Processing

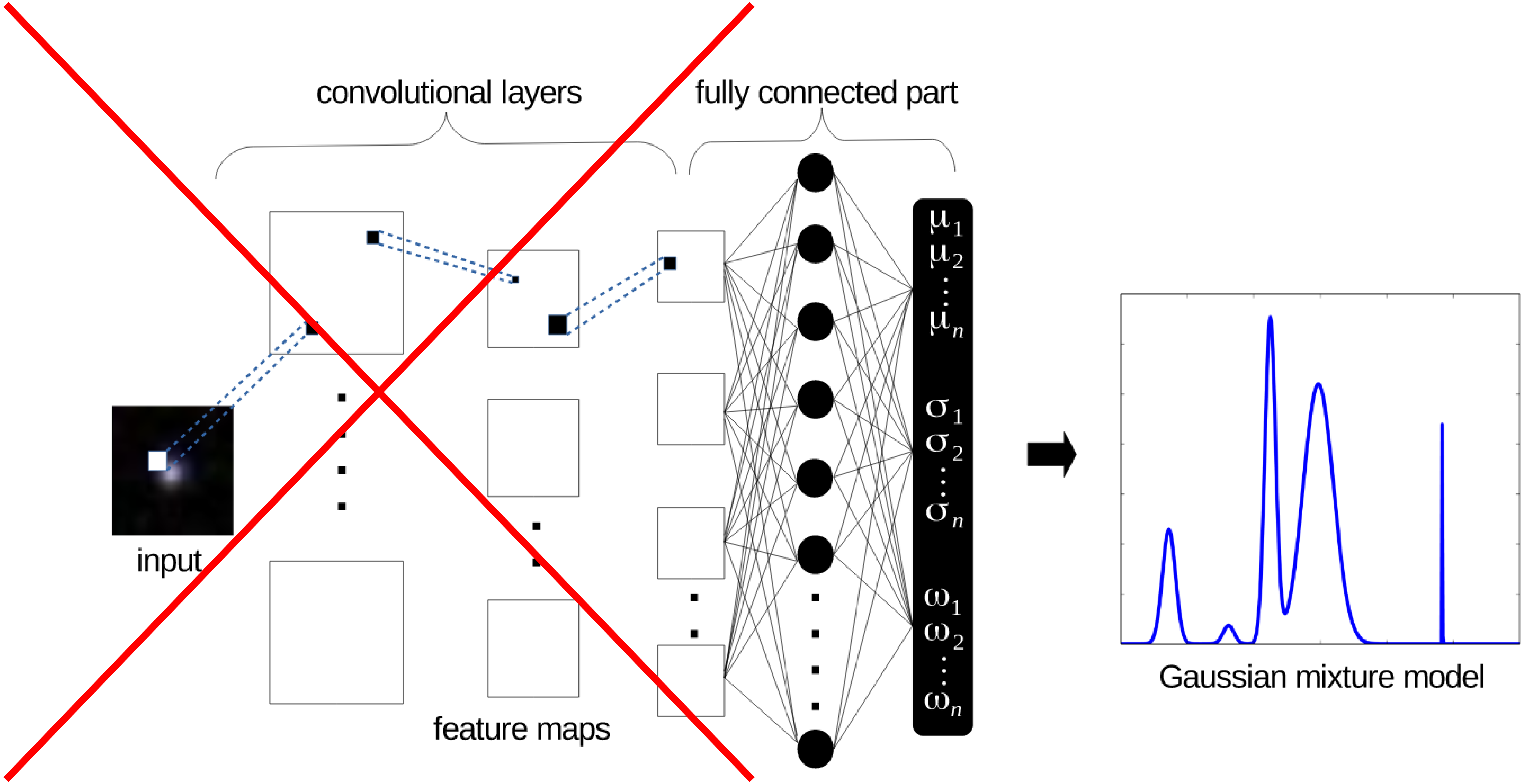
to predict for single stations

- 537 stations with measurements
  - (lat, long, alt, orog., land/sea)
- 48h forecast lead time
- 18 x 2 parameters (mean, stddev)
- 2007-2015 for training
- 2016 for testing

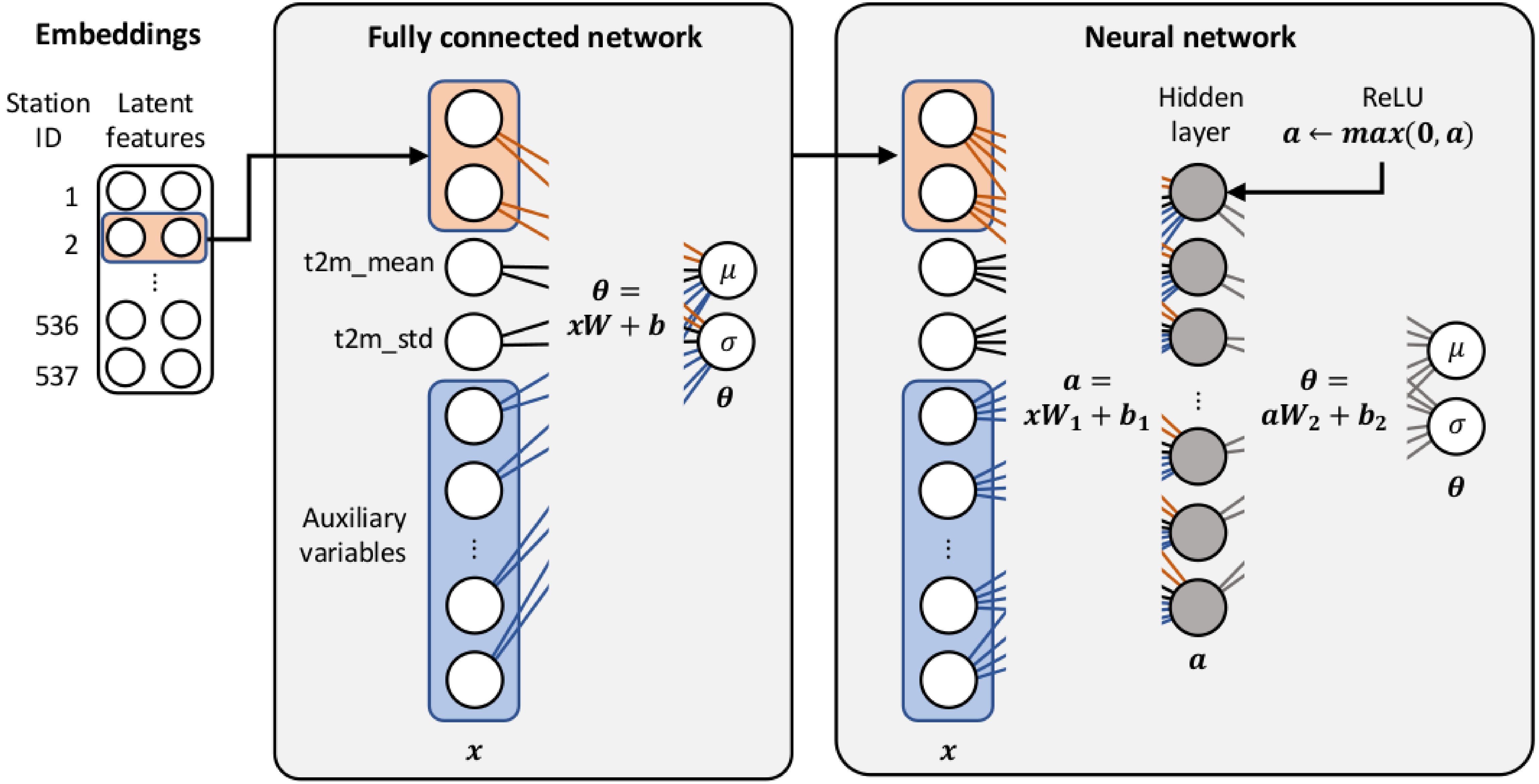
with best method CRPS=0.81



DCN meet MDN


convolutional layers
fully connected part
input
feature maps
μ_1
μ_2
μ_n
σ_1
σ_2
σ_n
ω_1
ω_2
ω_n
Gaussian mixture model

Using ~~DC~~MDN

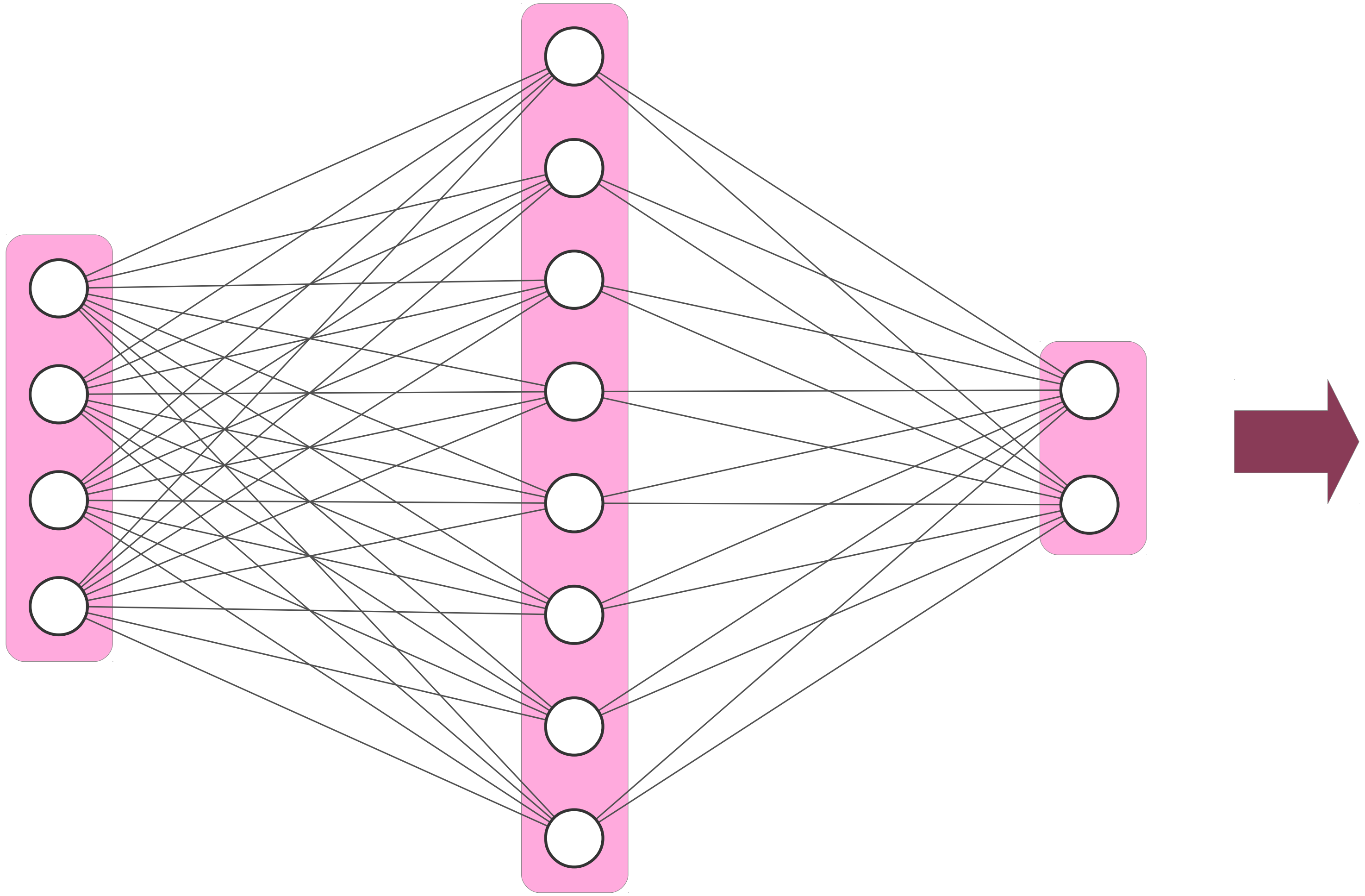


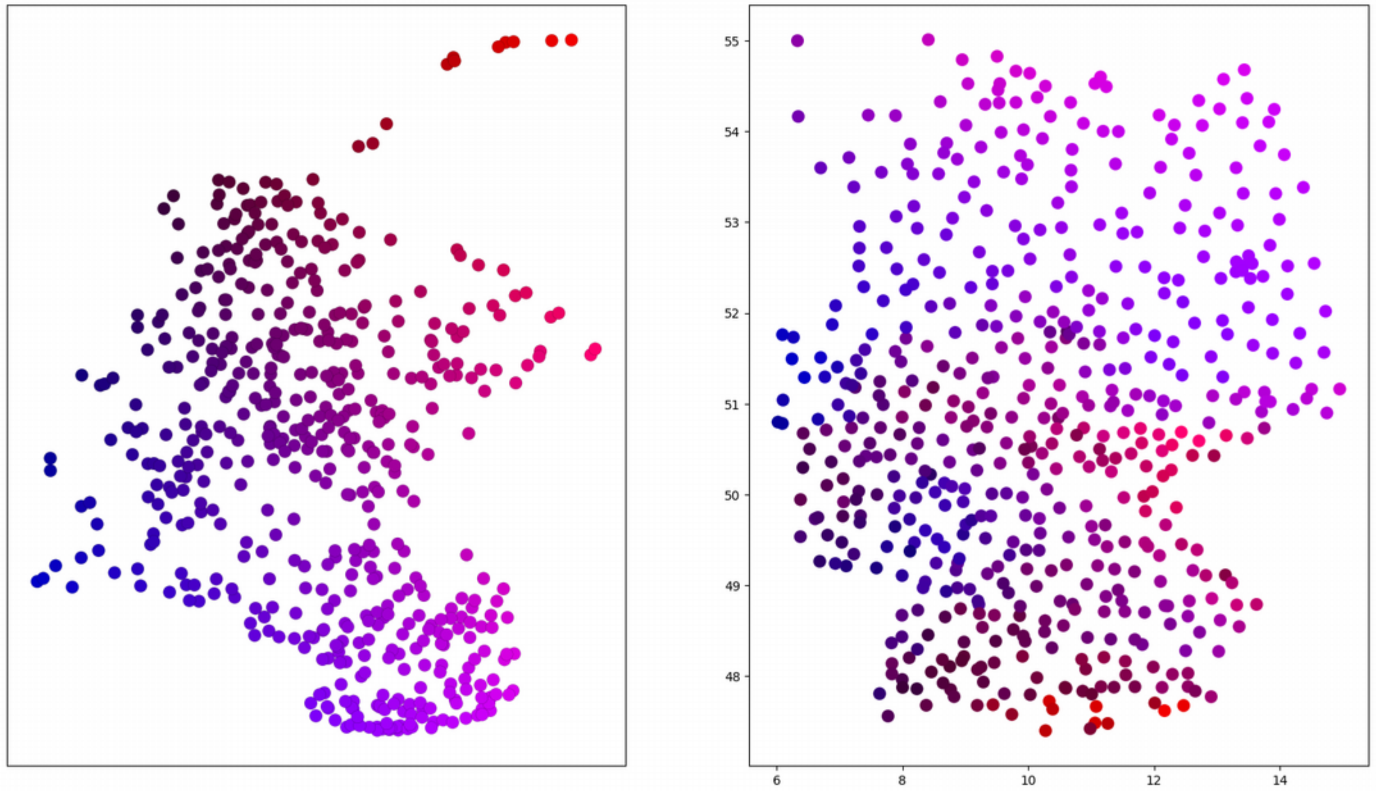
Rasp and Lerch 2018

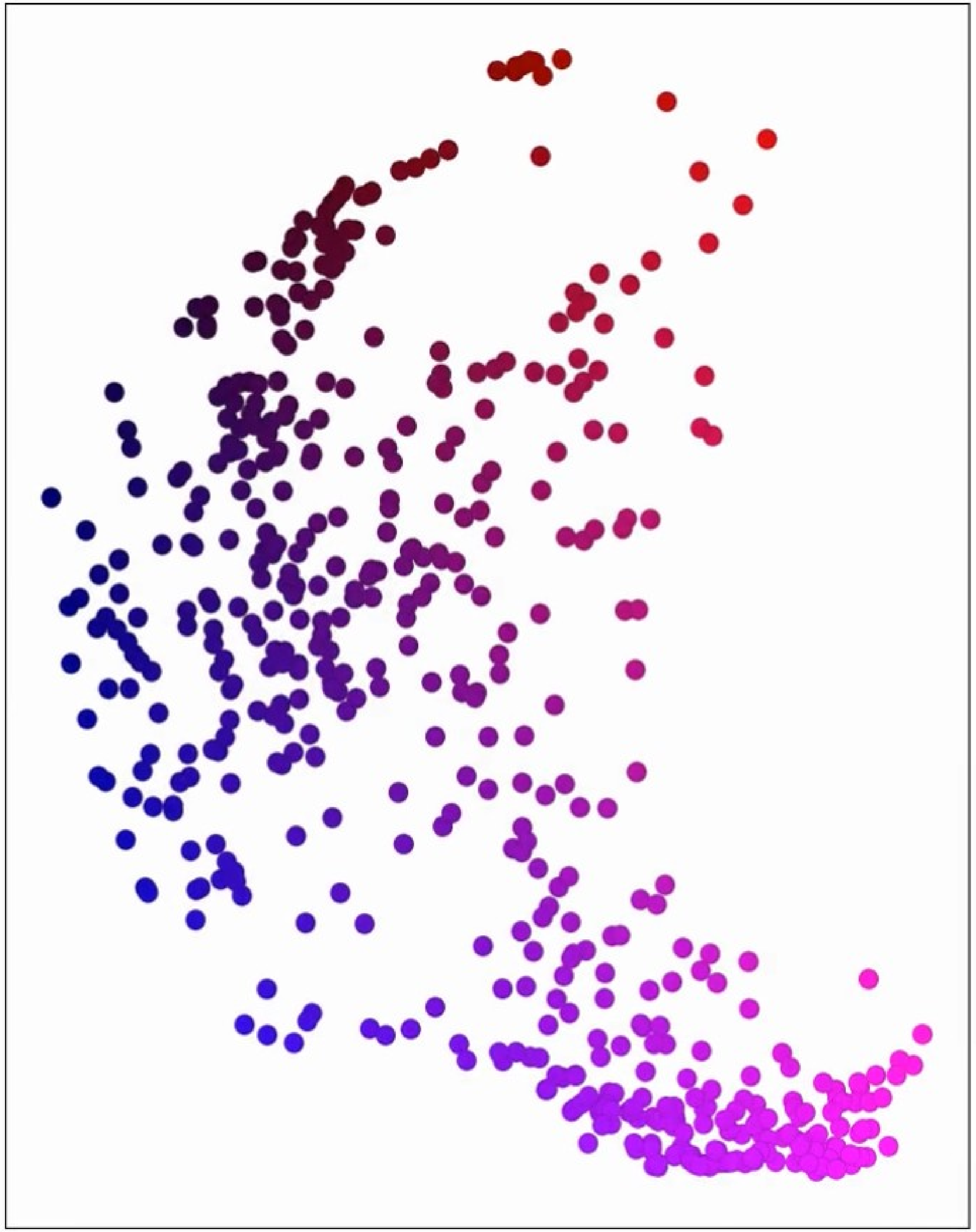
CRPS=0.78

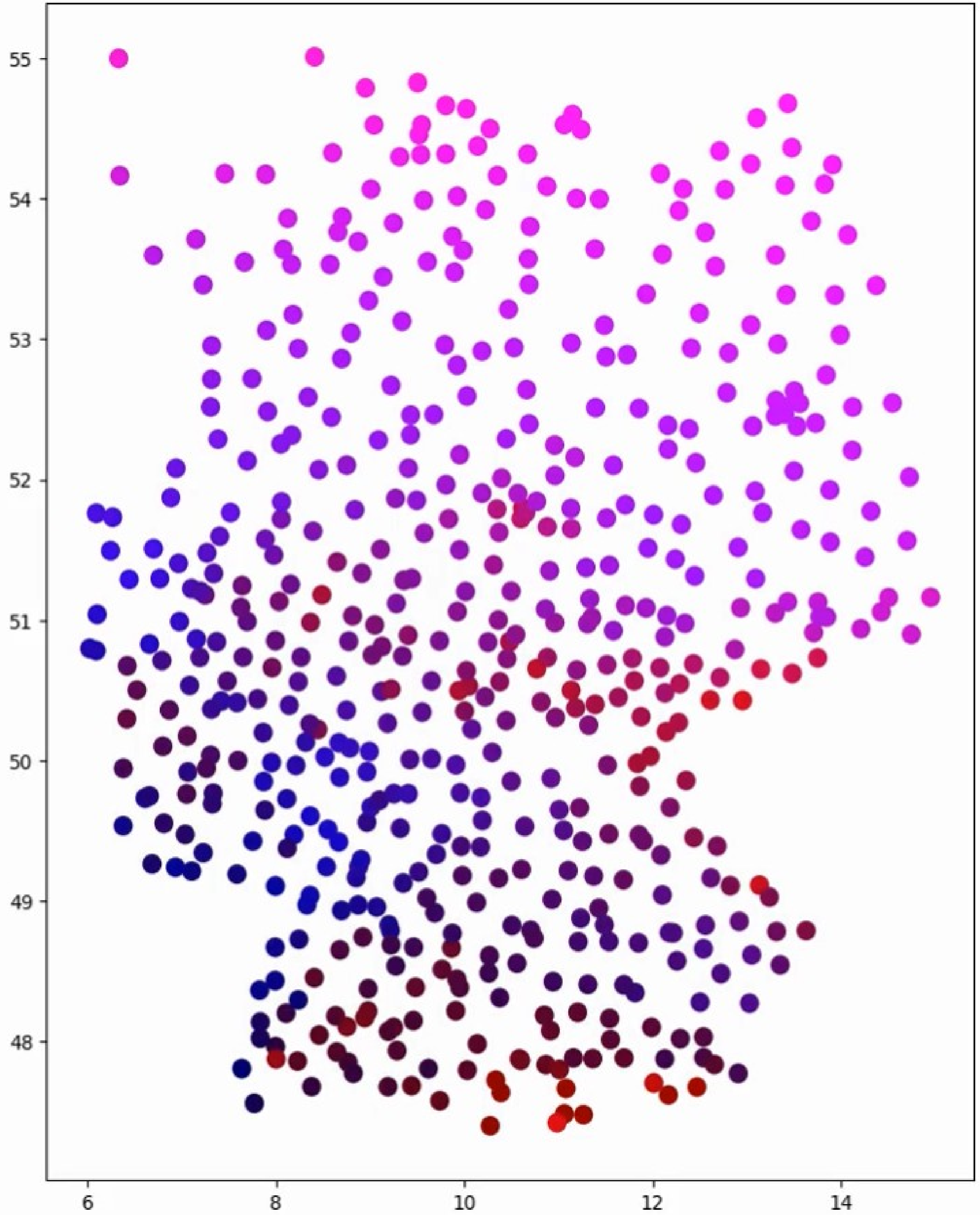
Projecting Station Parameters

latitude, longitude, altitude, orography







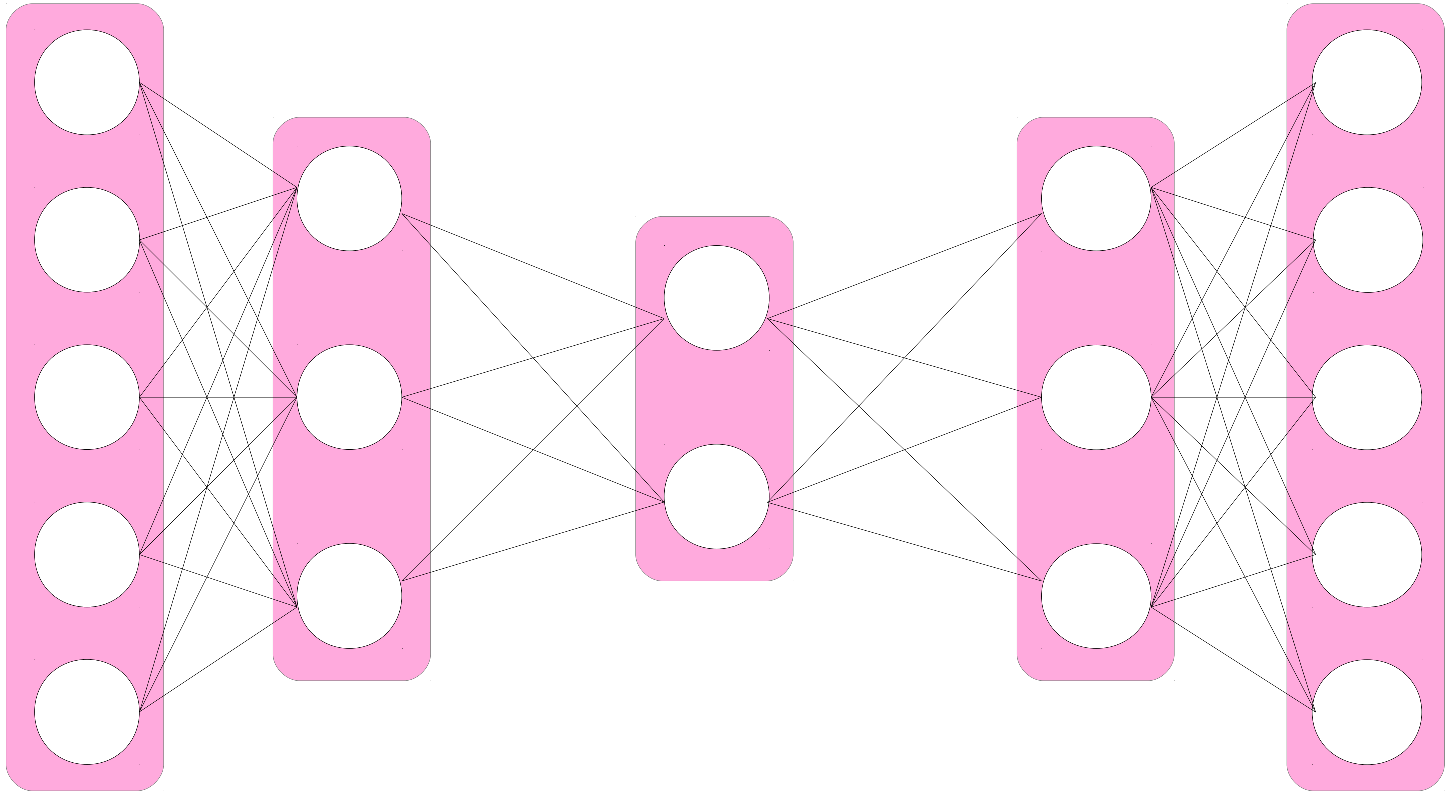

55
54
53
52
51
50
49
48
6
8
10
12
14

More Complex Network

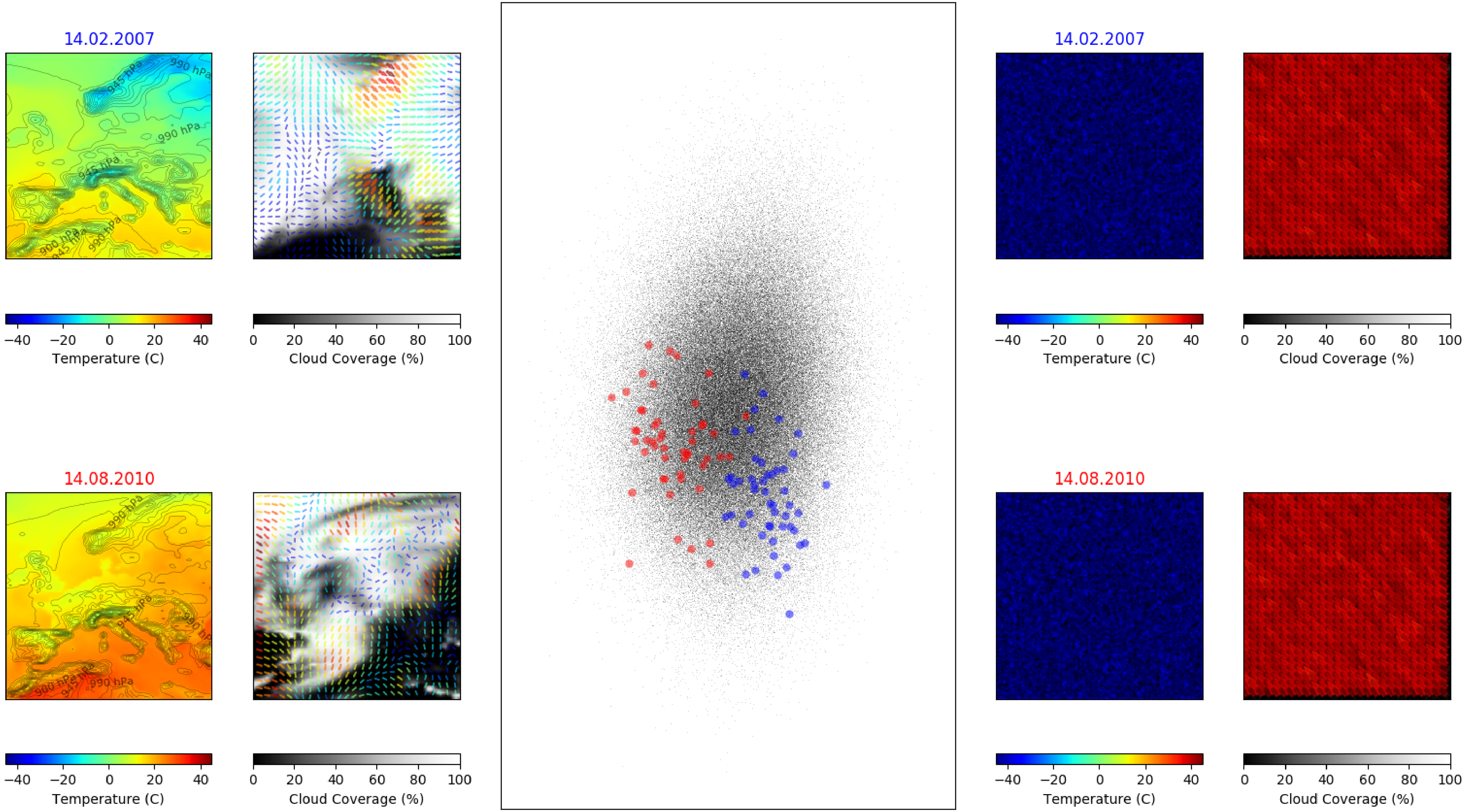
DCMDN → whole ensemble 50*81*81*17 * 535 * 3667

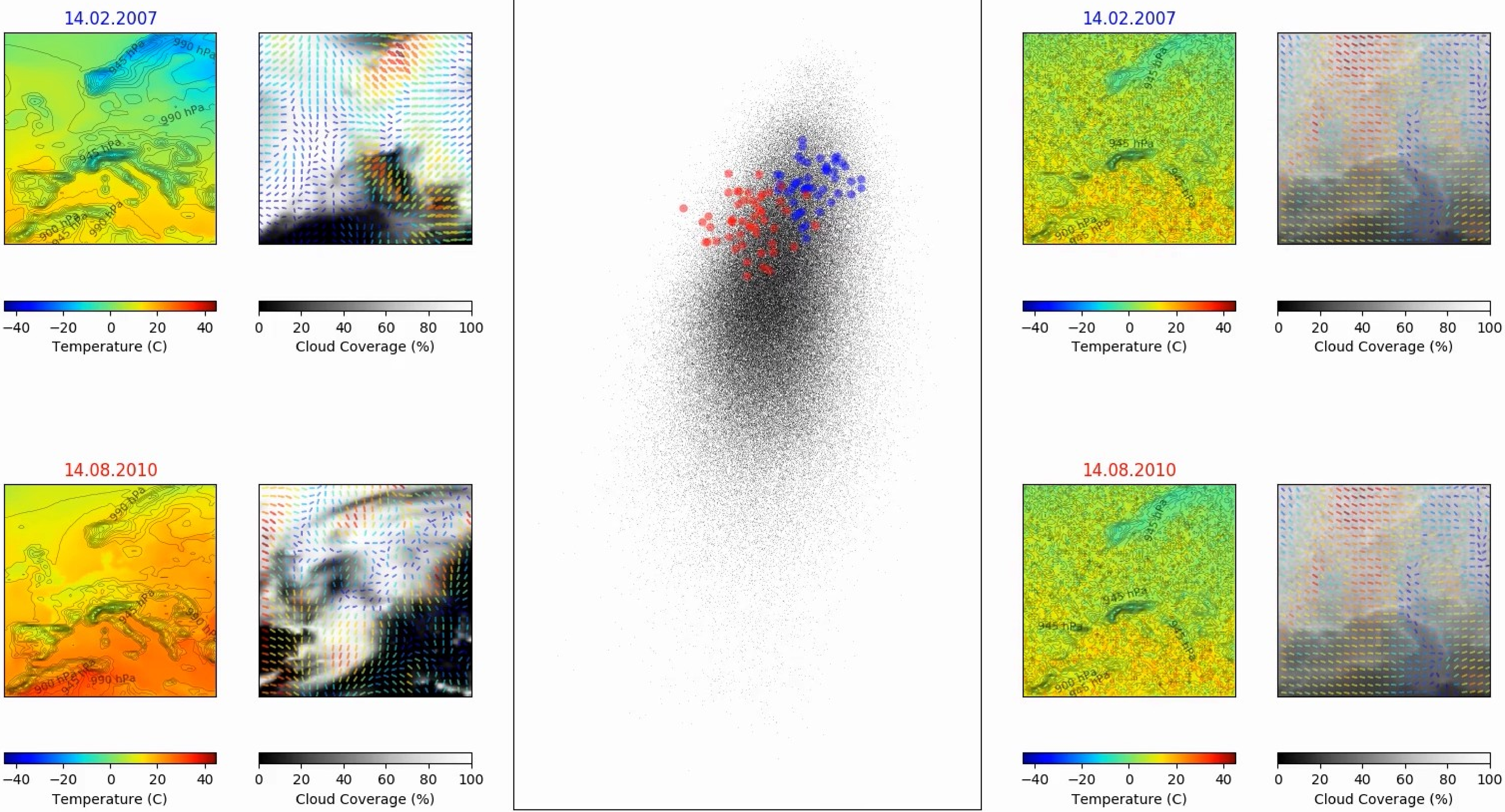
- not enough data for training

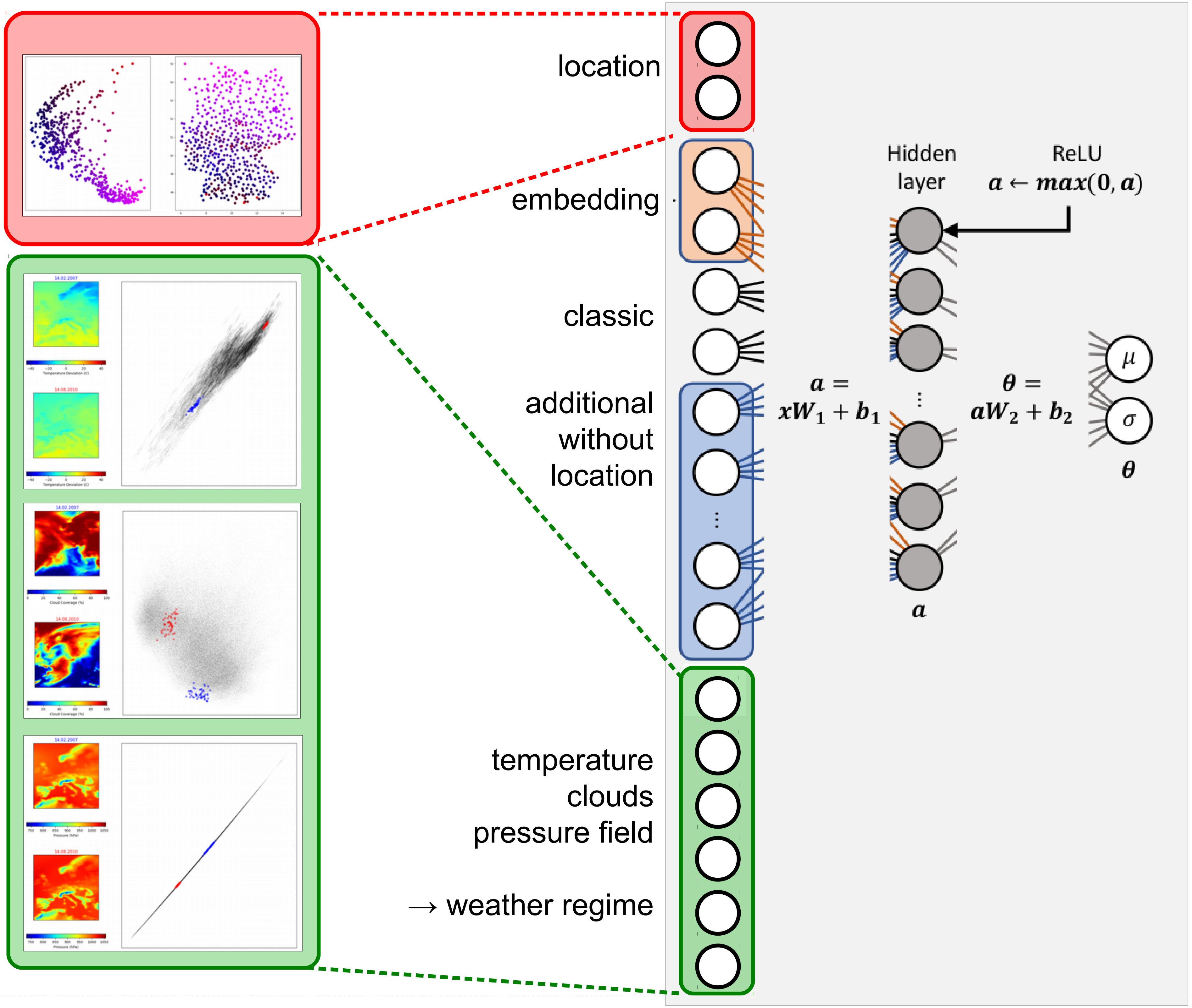
Use different strategy with autoencoders



Projecting Forecast Ensembles




14.02.2007
990 hPa
945 hPa
900 hPa
−40 −20 0 20 40
Temperature (C)
0 20 40 60 80 100
Cloud Coverage (%)
14.08.2010
−40 −20 0 20 40
Temperature (C)
0 20 40 60 80 100
Cloud Coverage (%)
14.02.2007
−40 −20 0 20 40
Temperature (C)
0 20 40 60 80 100
Cloud Coverage (%)
14.08.2010
−40 −20 0 20 40
Temperature (C)
0 20 40 60 80 100
Cloud Coverage (%)


location
embedding
classic
additional
without
location
temperature
clouds
pressure field
→ weather regime
Hidden
layer
ReLU
$a \leftarrow max(0, a)$
$a = xW_1 + b_1$
$\theta = aW_2 + b_2$
μ
σ
θ
a

CRPS=0.76

Conclusion

Compressing complex data might add interpretability

Use of proper scores for training helps a lot → CRPS