Self-Adaptive Optimization of Ocean Observing Networks

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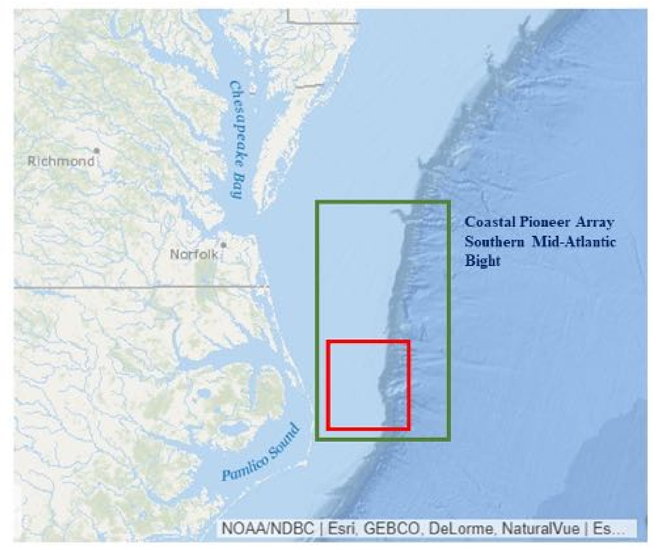
Lack of active learning epistemic uncertainty within the ocean observation community.

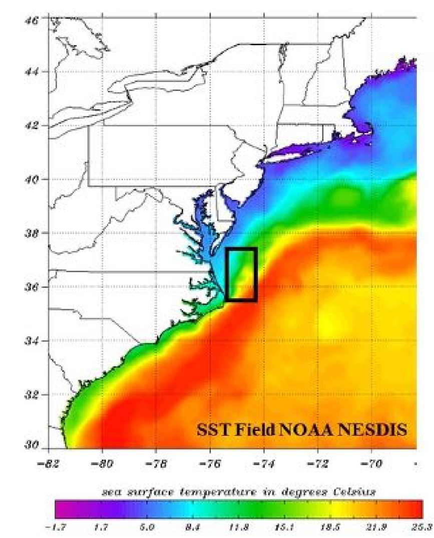
Spatiotemporal learning heterogeneity enable knowledge transfer from one site to another.

Explainable AI and graphical deep learning integrate multimodal sensory data.

OVERVIEW

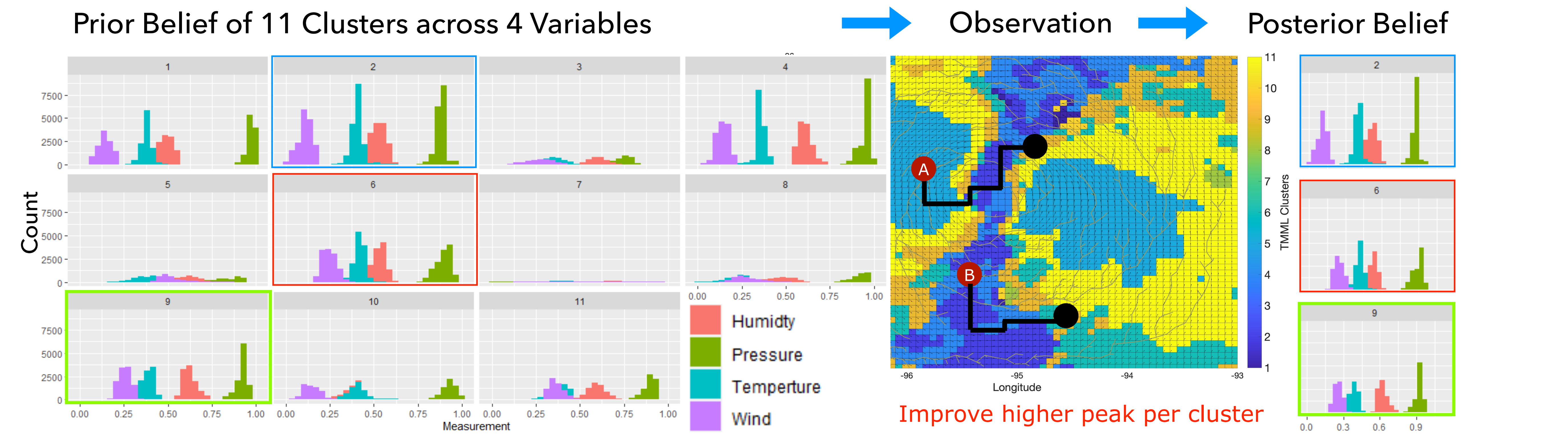
- Traditional models train data precisely and implement it according to the fit principle without addressing dynamics/uncertainties.
- Heterogeneous time-serial data limits transferring parameters to different locations.
- In this project, the knowledge discovery of heterogeneity observed environmental variables and unobserved (unmeasured) variables will improve the prediction accuracy.
- A prototype of Hurricane digital twin is presented.





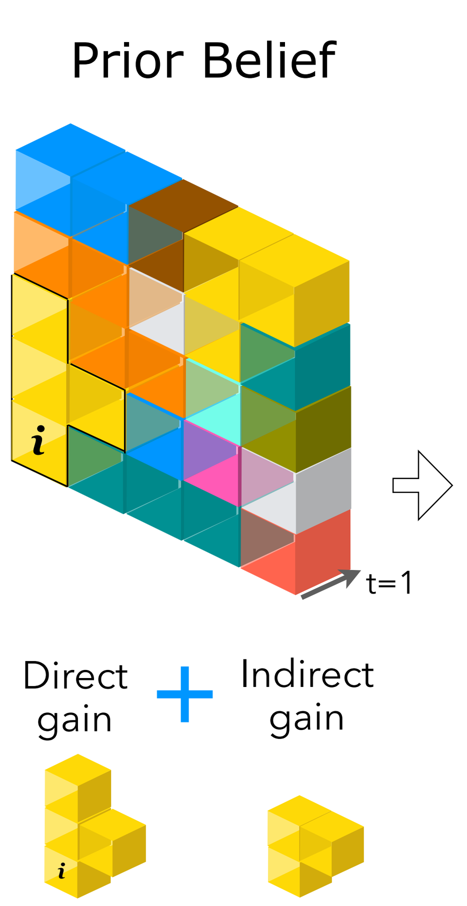
LEARNING STORM

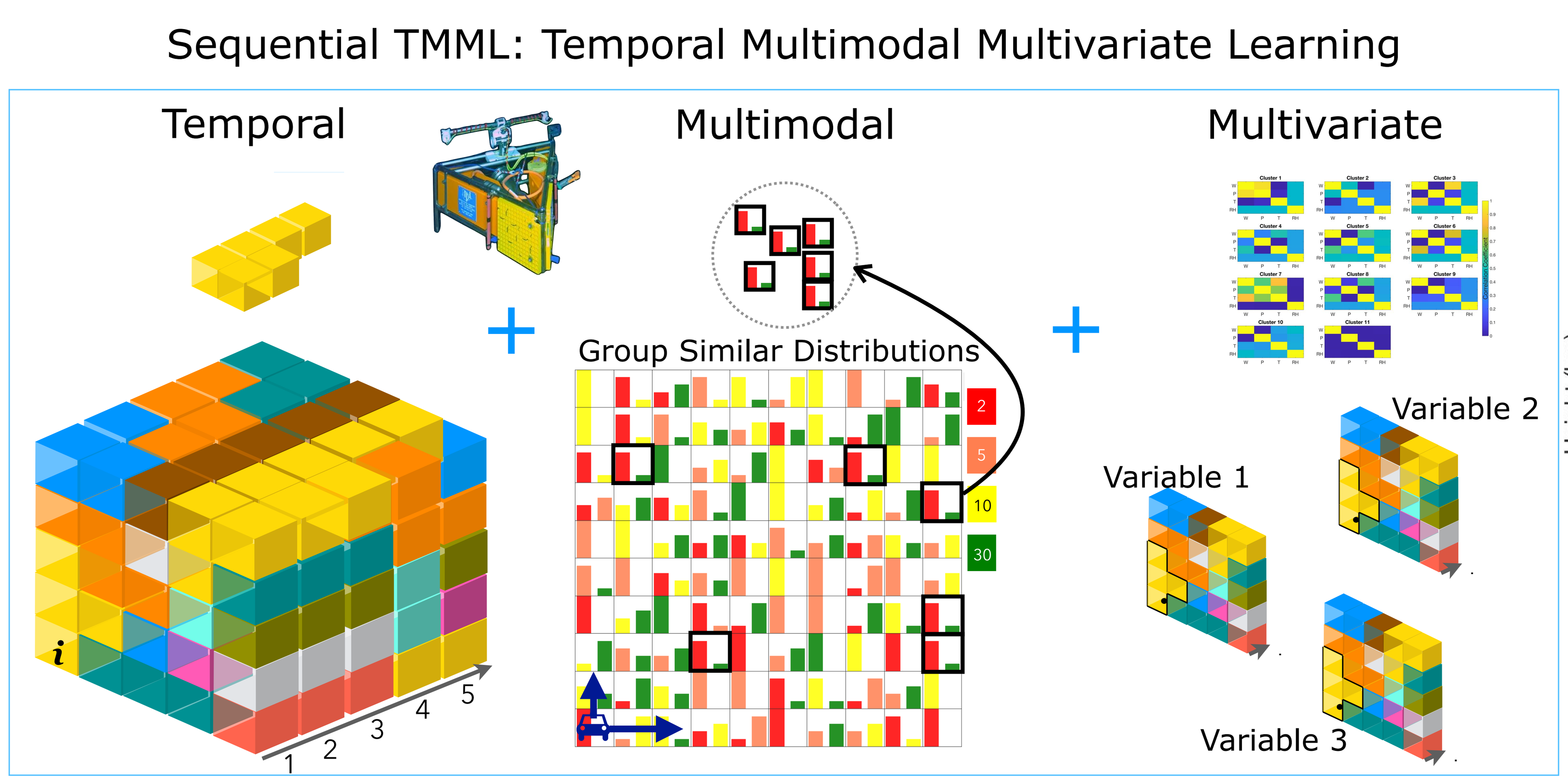
- Posterior probability distribution each variable/cluster narrower less uncertainty.

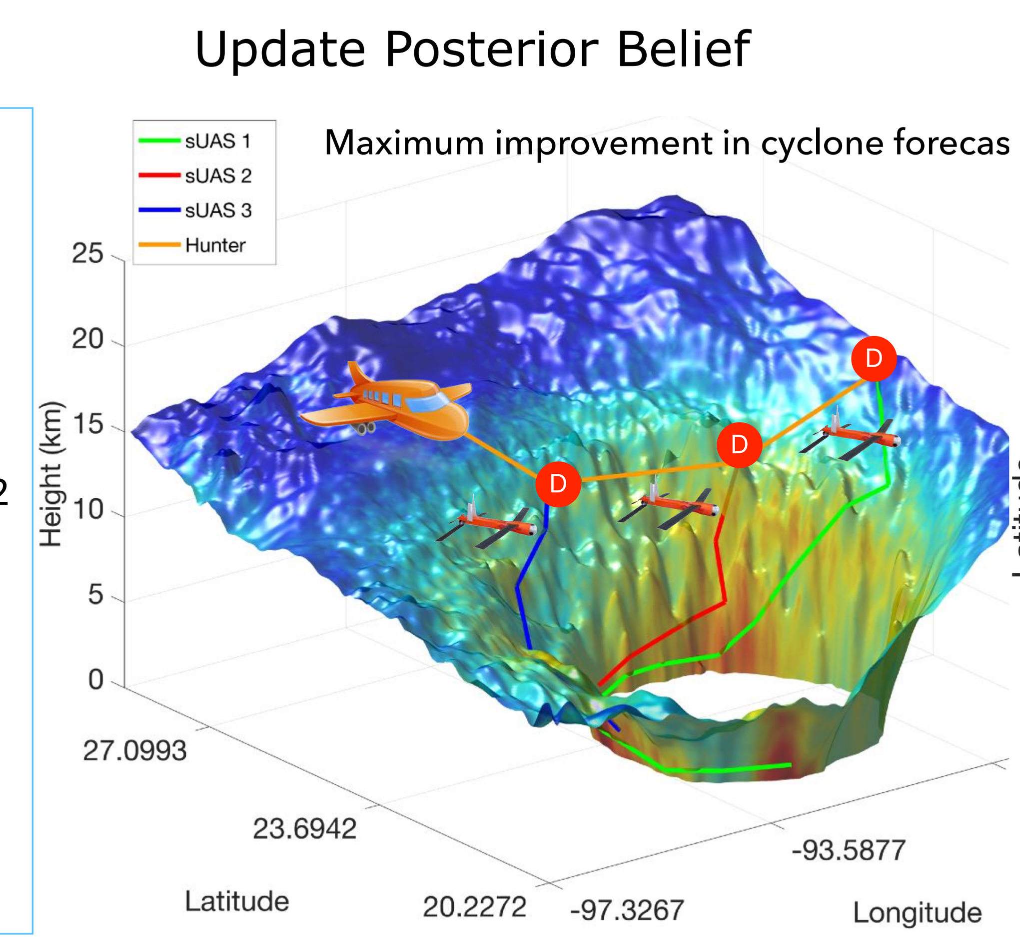


TMML

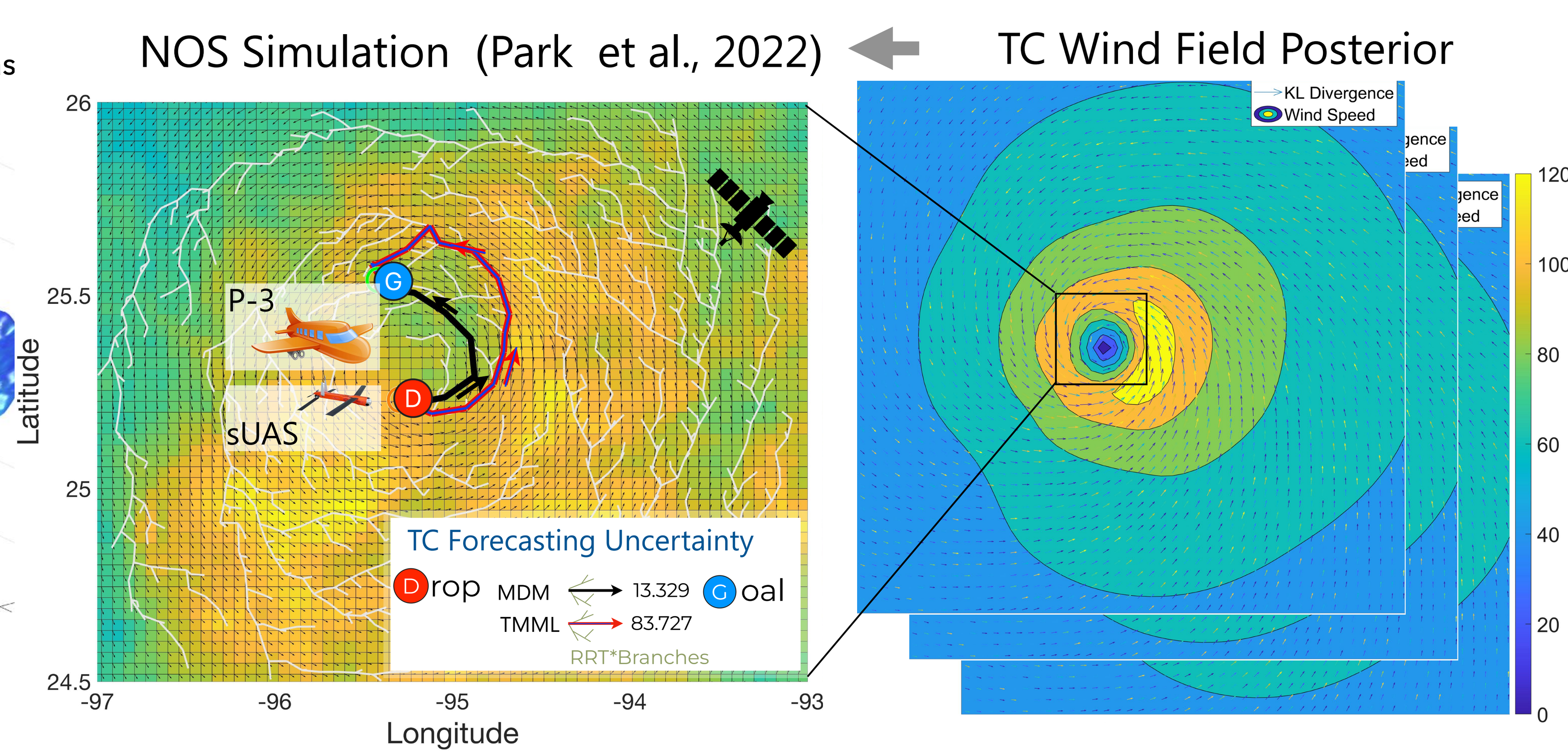
- An online gain in temporal, multimodal, and multivariate prediction uncertainty between prior and posterior.
- Each cell has a combination of discrete travel time distributions (i.e., 2, 5, 10, 30min) with different weights.







- Safe and efficient sUAS path solution on centered horizontal cross-sections for Hurricane Harvey - observations greatly improved the prediction
- Multiagent utility guided observations constituted from multivariate entropy.



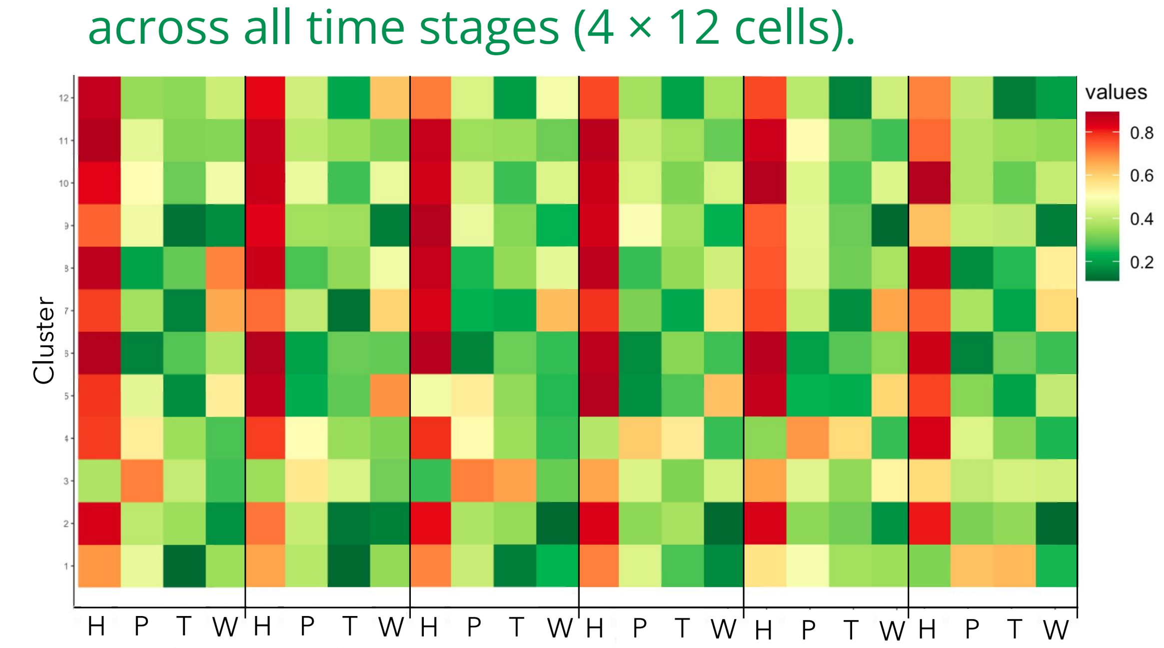
ONLINE TMML

- Time-dependent realization of uncertainties measure how well multinomial posterior $q\lambda(z|x)$ approximates the true posterior $p(z|x)$, using KL divergence $KL(q\lambda(z|x)||p(z|x))$.
- Online learning sequentially updates rapidly exploring random tree star (RRT*).
- Vehicle traverses path, observations are made and variational Bayesian inference generates a posterior belief given the prior belief of cell type distributions within each cluster.

Algorithm 1 :TMML-RRT* with Online Recourse

```
T ← InitializeTree()
T ← InsertNode(∅, z_init, T)
for i=0 to i=N do
    z_rand ← Sample(i)
    z_nearest ← NearestTMML(T, z_rand)
    (z_new, U_new) ← Steer(z_nearest, z_rand)
    if NoExceed(z_new) then
        z_near ← Near(T, z_new, |V|)
        z_max ← ChooseParentTMML(z_near, z_nearest, z_new)
        T ← InsertNode(z_max, z_new, T)
        T ← Rewire(T, z_near, z_max, z_new)
    end if
end for
OptPath ← OnlineRecourse(T, n_s, n_g)
```

- Clustered TMML distribution of four variables across all time stages (4 × 12 cells).



- One observation of temperature within cluster 1 at time 1 are used in removing prediction uncertainties of humidity in cluster 2 at time 3.

CONCLUSIONS

- A new family of RL indirectly learn and transfer TMML information.

Shortest (MDM) = 2.36%		Non Temporal		Temporal
		Unimodal	Multimodal	
Correlation	Univariate	2.66%	4.34%	-
	Multivariate	3.28%	6.25%	11.26%
Deep	Multivariate	-	7.37%	**13.45%**

- Average improvement in predicted multimodal measurement was significantly higher when TMML were considered.
- TMML solve challenging tasks where the uncertainty is revealed in a sequence by grouping samples within similar distribution types and inferring the posterior based on expected observations.