

Clustering Fine-Scale River Network Topologies for Use in Earth System Models

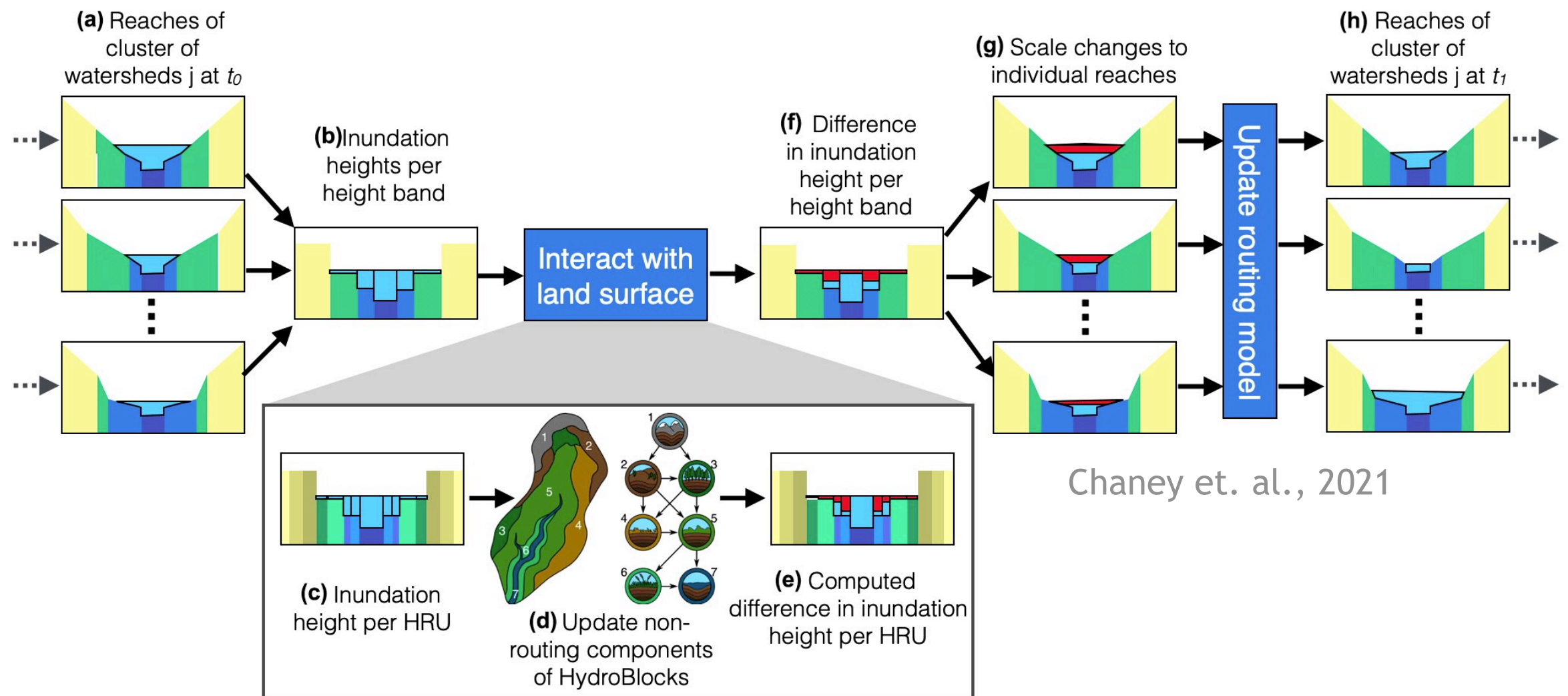
Laura Torres-Rojas, Noemi Vergopolan,
Daniel Guyumus, Nathaniel Chaney



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Motivation

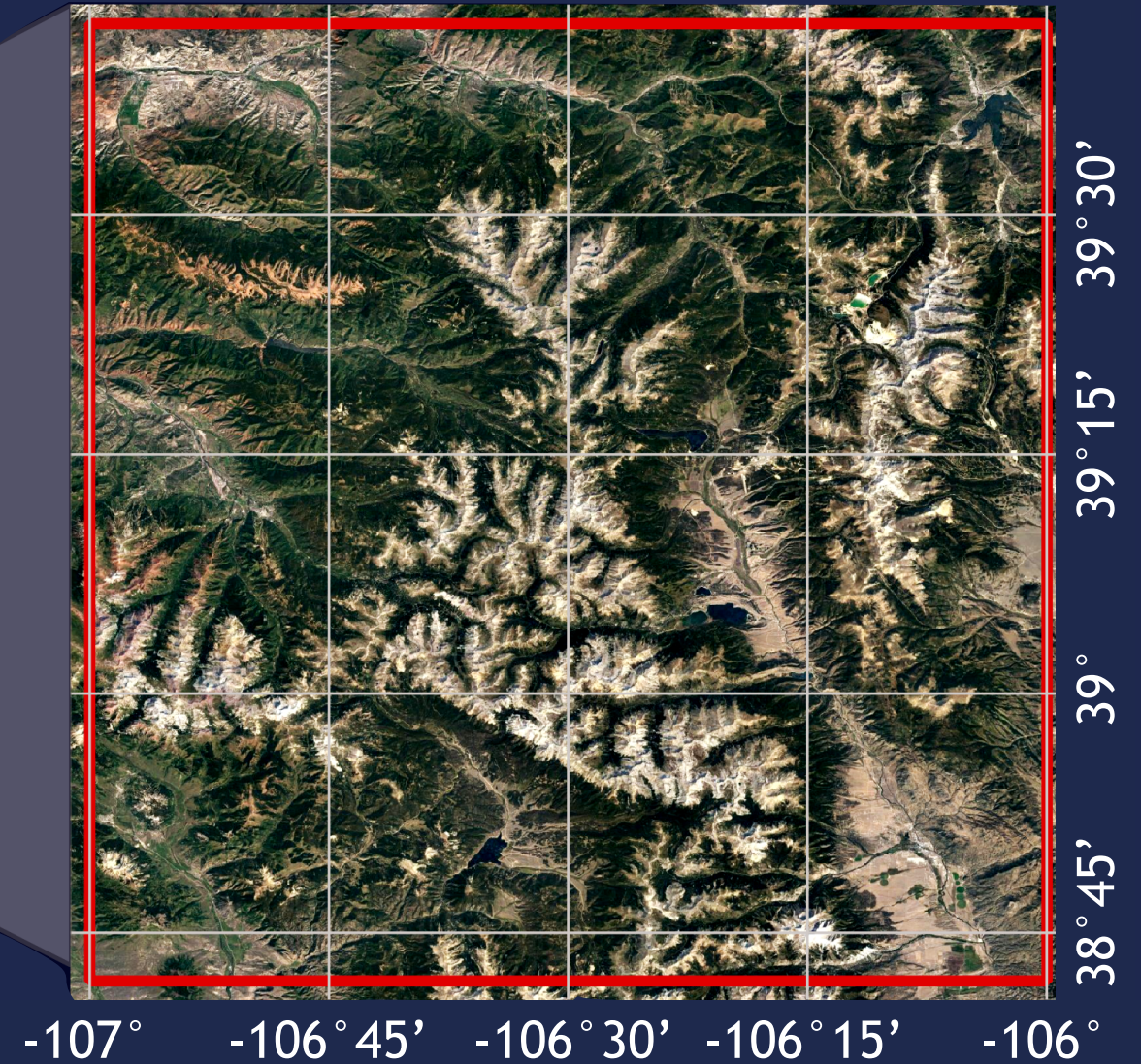
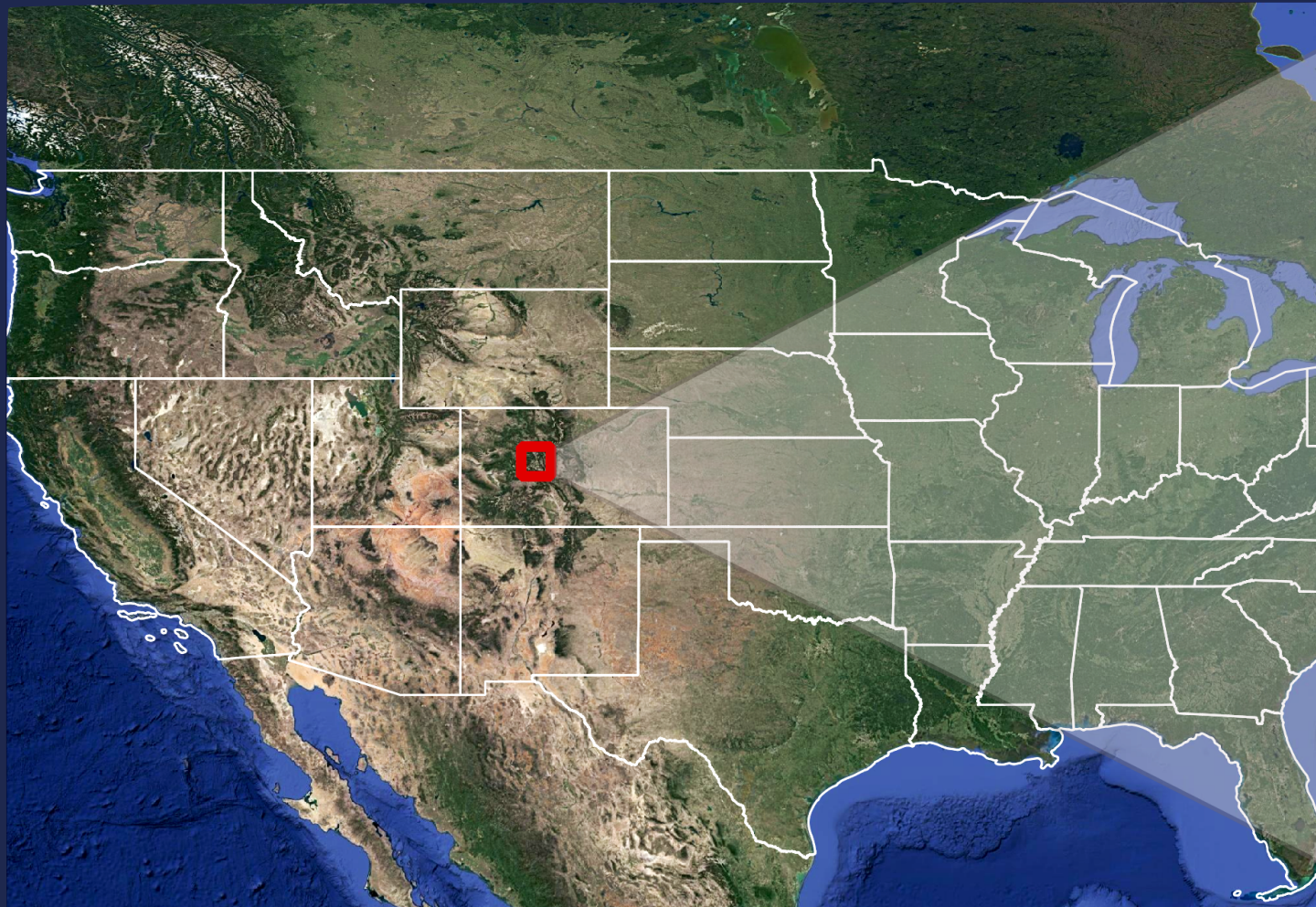
- Fully distributed vs. Semi-distributed modeling approaches.
- HydroBlocks Land Surface Model**
- Limitation routing: Manageable for ~5,000 channels.



Goal: Simplified structure of river network: Scalability over continental scales.

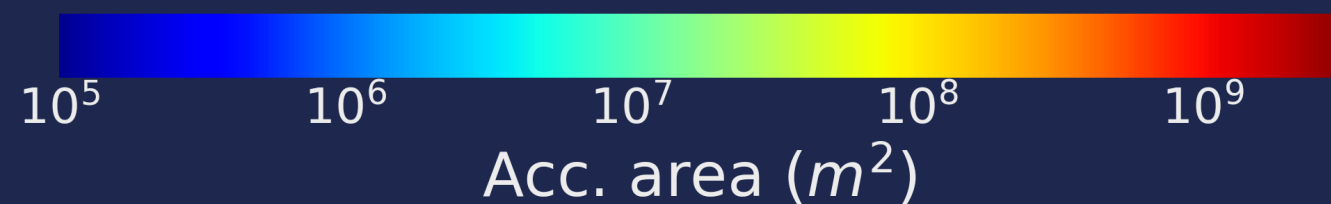
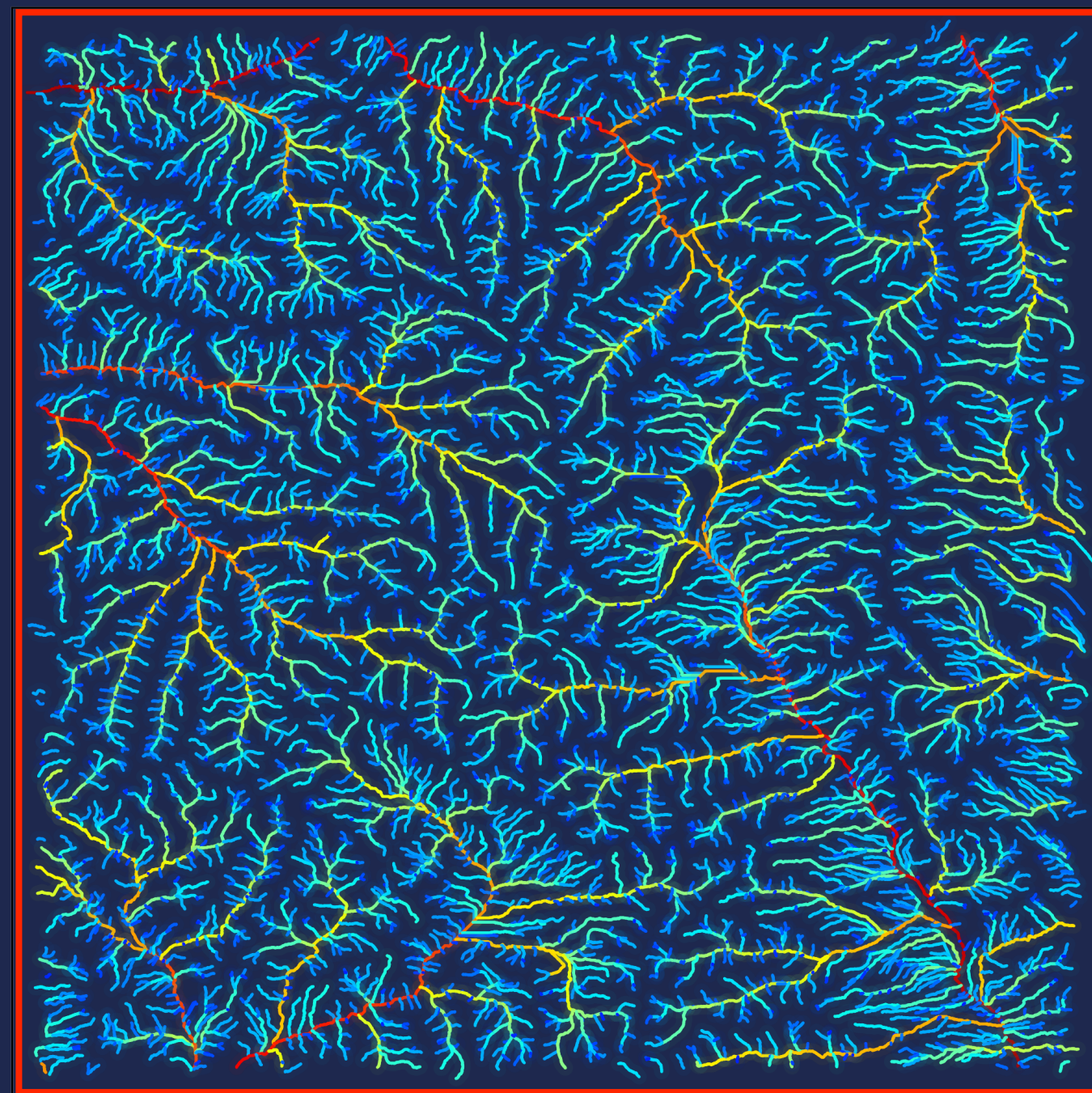
Study area

1x1 domain, centered in Mt. Elbert, CO



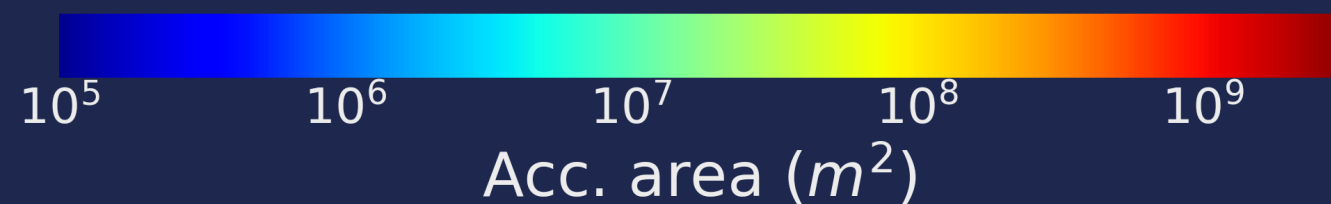
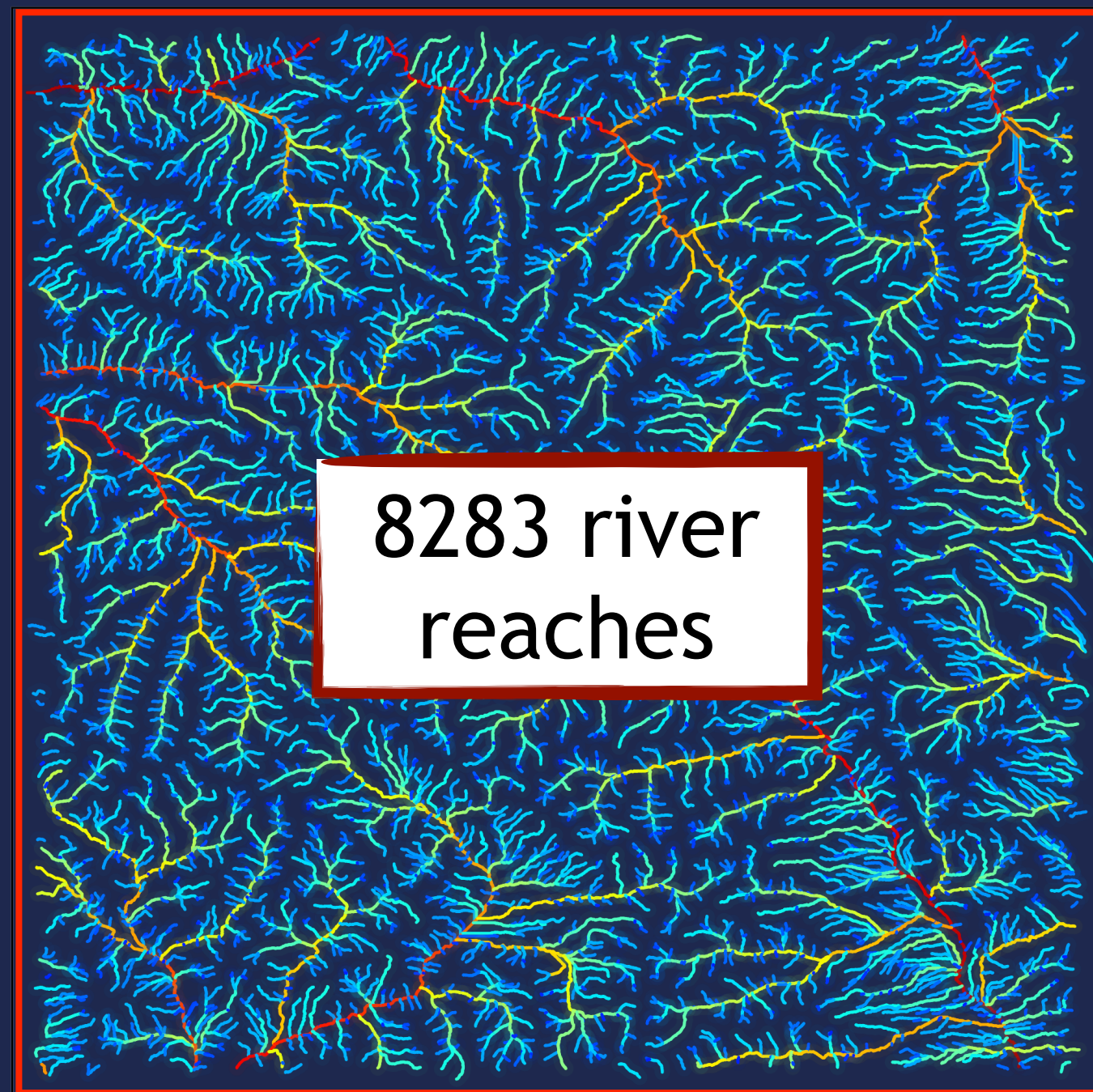
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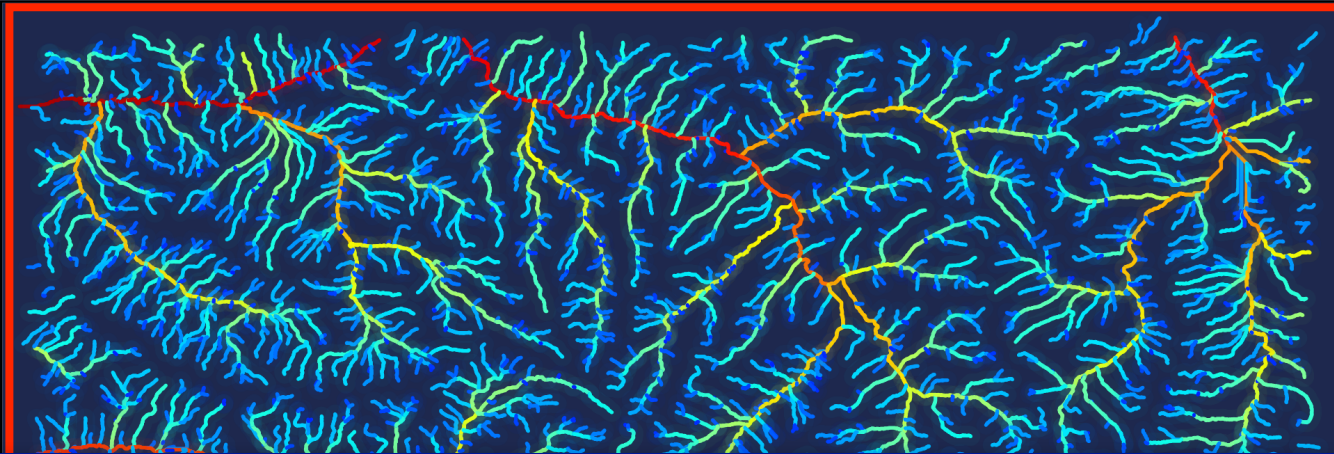
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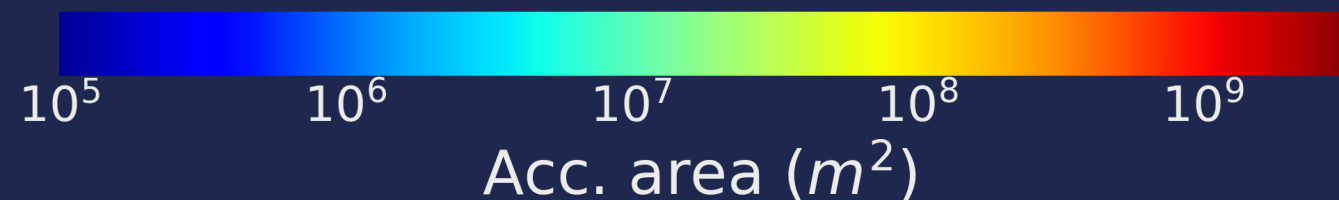
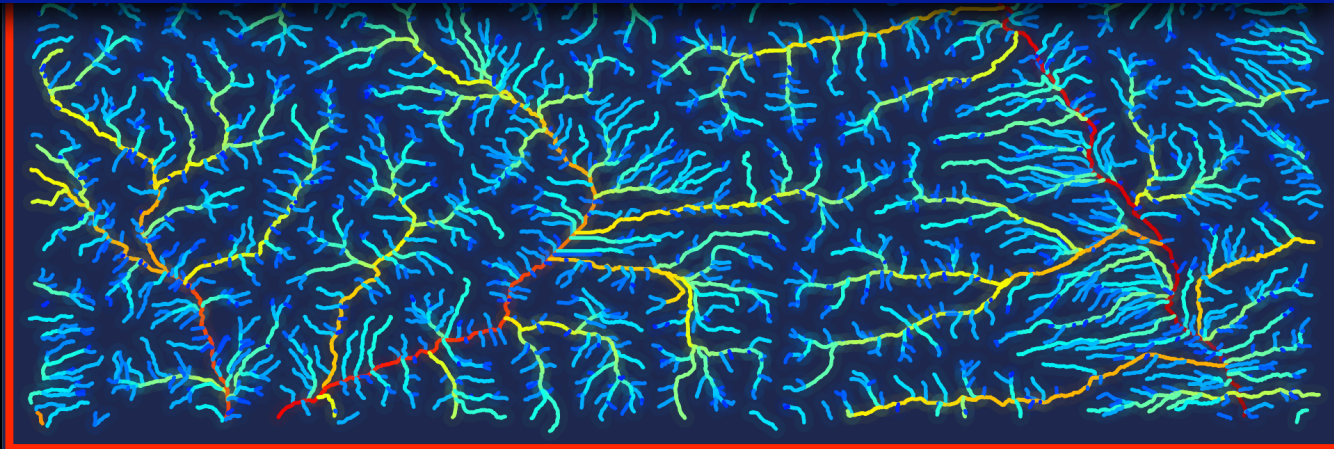


Study area

1x1 domain, centered in Mt. Elbert, CO

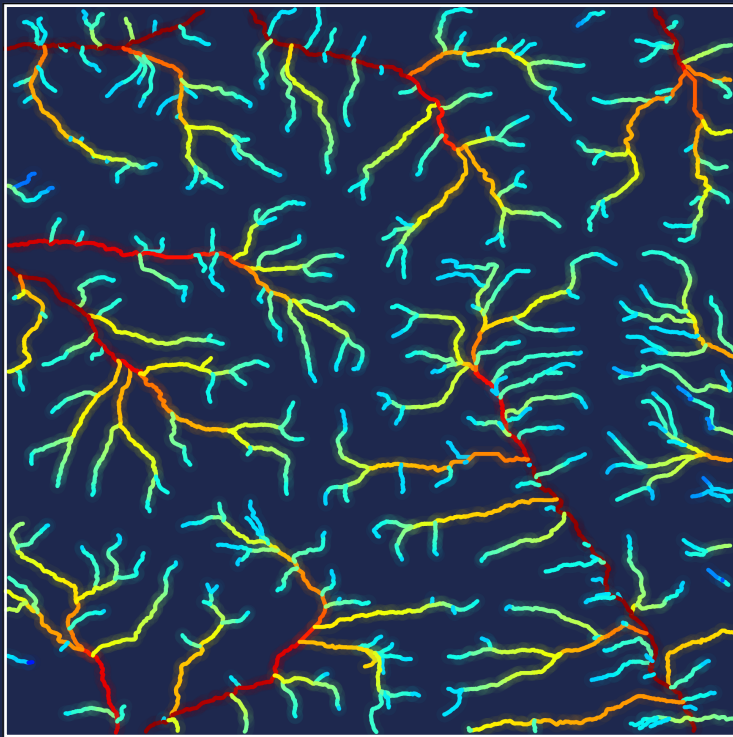


Idea: Cluster repeating patterns of subnetworks' topologies and solve for “characteristic topologies”.

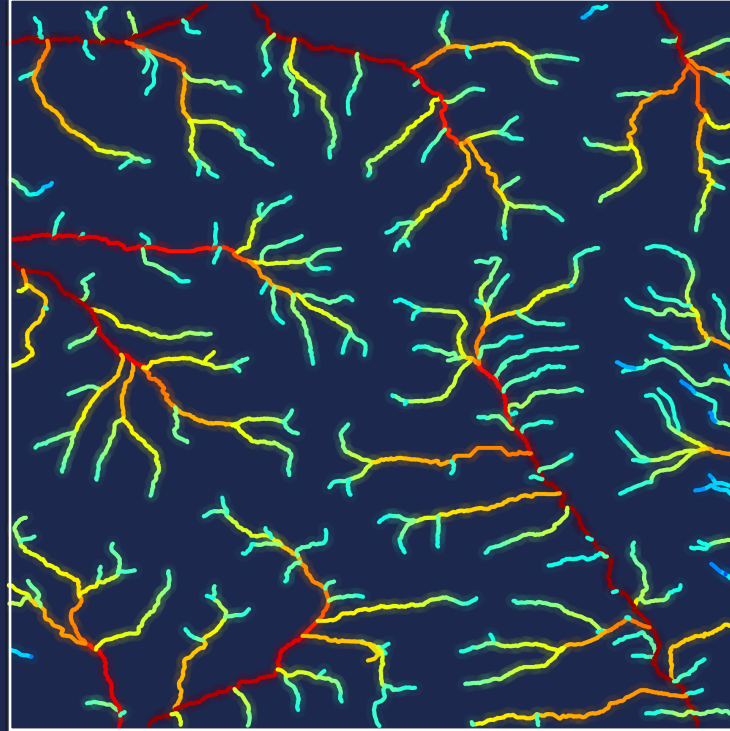


Stage 1: Select reaches to solve explicitly

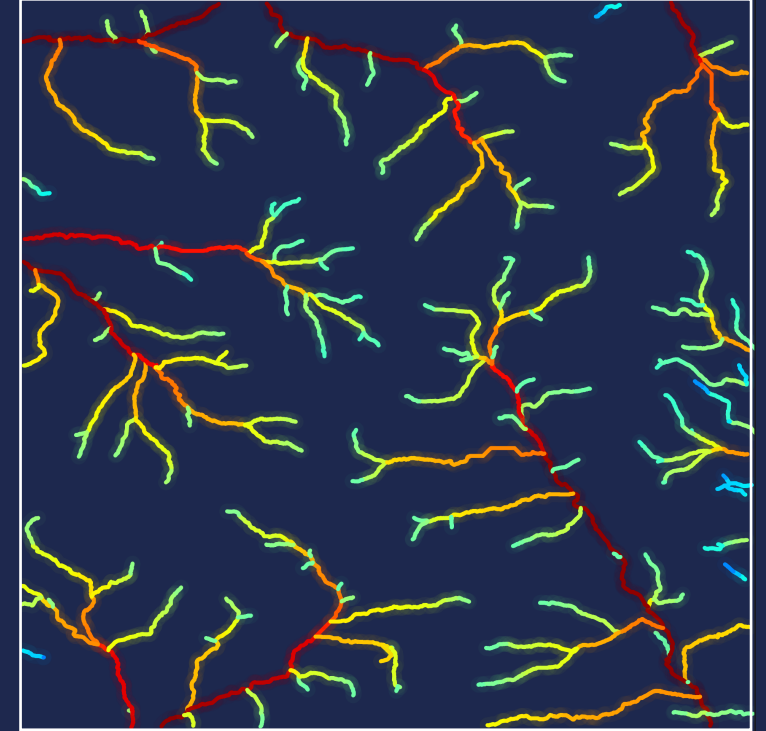
$p_{acc} = 70\%$



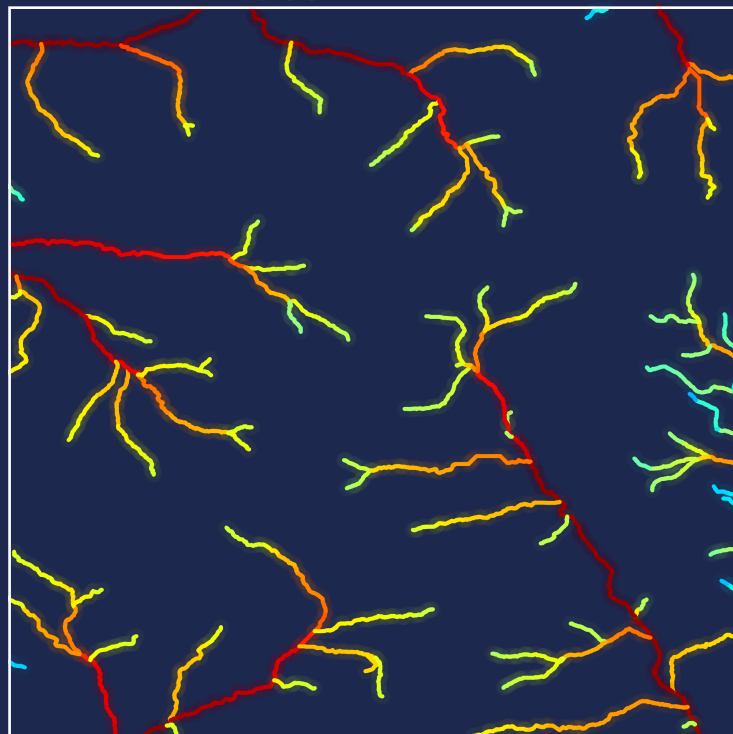
$p_{acc} = 75\%$



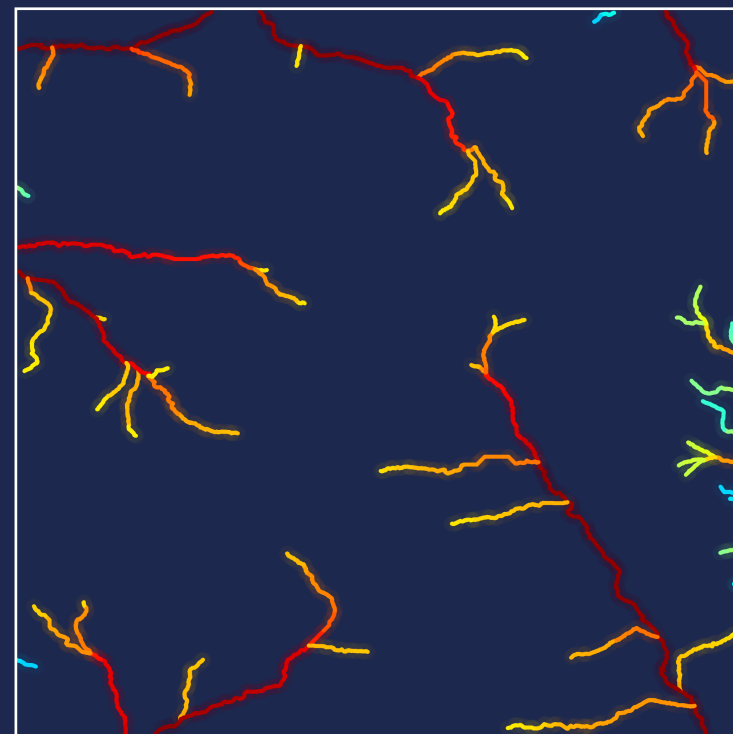
$p_{acc} = 80\%$



$p_{acc} = 85\%$



$p_{acc} = 90\%$



Stage 2: Clustering topologies

2.1. 35 descriptors of subnetwork topologies

Number of reaches ($n_{reaches}$)	Average bankfull width (μ_{BF})	Average sub-basin elevation (μ_{DEM})	Nullity, unweighted (N_{uw})	Spectral gap, w=slope ($G_{w=S}$)
Total length (ΣL)	Average drainage density (μ_{D_d})	Average sub-basin topological index (μ_{TI})	Nullity, w=1/length ($N_{w=\frac{1}{L}}$)	Wiener number, unweighted (W_{uw})
Total acc. area (ΣAcc)	Max. Drainage density (Max_{D_d})	Average sub-basin aspect (μ_{Asp})	Nullity, w=width ($N_{w=W}$)	Wiener number, w=1/length ($W_{w=\frac{1}{L}}$)
Average length (μ_L)	Average Shreve order (μ_{ShrOrd})	Average shortest path length, w=width ($\mu_{SPL_{w=W}}$)	Nullity, w=slope ($N_{w=S}$)	Wiener number, w=width ($W_{w=W}$)
Average acc. area (μ_{Acc})	Max. Shreve order (Max_{ShrOrd})	Average shortest path length, w=slope ($\mu_{SPL_{w=S}}$)	Spectral gap, unweighted (G_{uw})	Wiener number, w=slope ($W_{w=S}$)
Average width (μ_W)	Average sinuosity (μ_S)	Average in-degree, w=width ($\mu_{D_{w=W}}$)	Spectral gap, w=1/length ($G_{w=\frac{1}{L}}$)	Global efficiency (G_{eff})
Average reach slope (μ_S)	Max. Sinuosity (Max_S)	Average in-degree, w=slope ($\mu_{D_{w=S}}$)	Spectral gap, w=width ($G_{w=W}$)	Global reaching centrality (GRC)

Channel features	Sub-basin aggregated properties	Spectral properties	Classical river network morphology	Graph-theory
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Stage 2: Clustering topologies

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Total acc. area (ΣA)	Max. Drainage density (Max_{D_d})	Average sub-basin aspect (μ_{Aspect})	Nullity, w=width ($N_{w=W}$)	Wiener number, w=1/length ($W_{w=\frac{1}{L}}$)

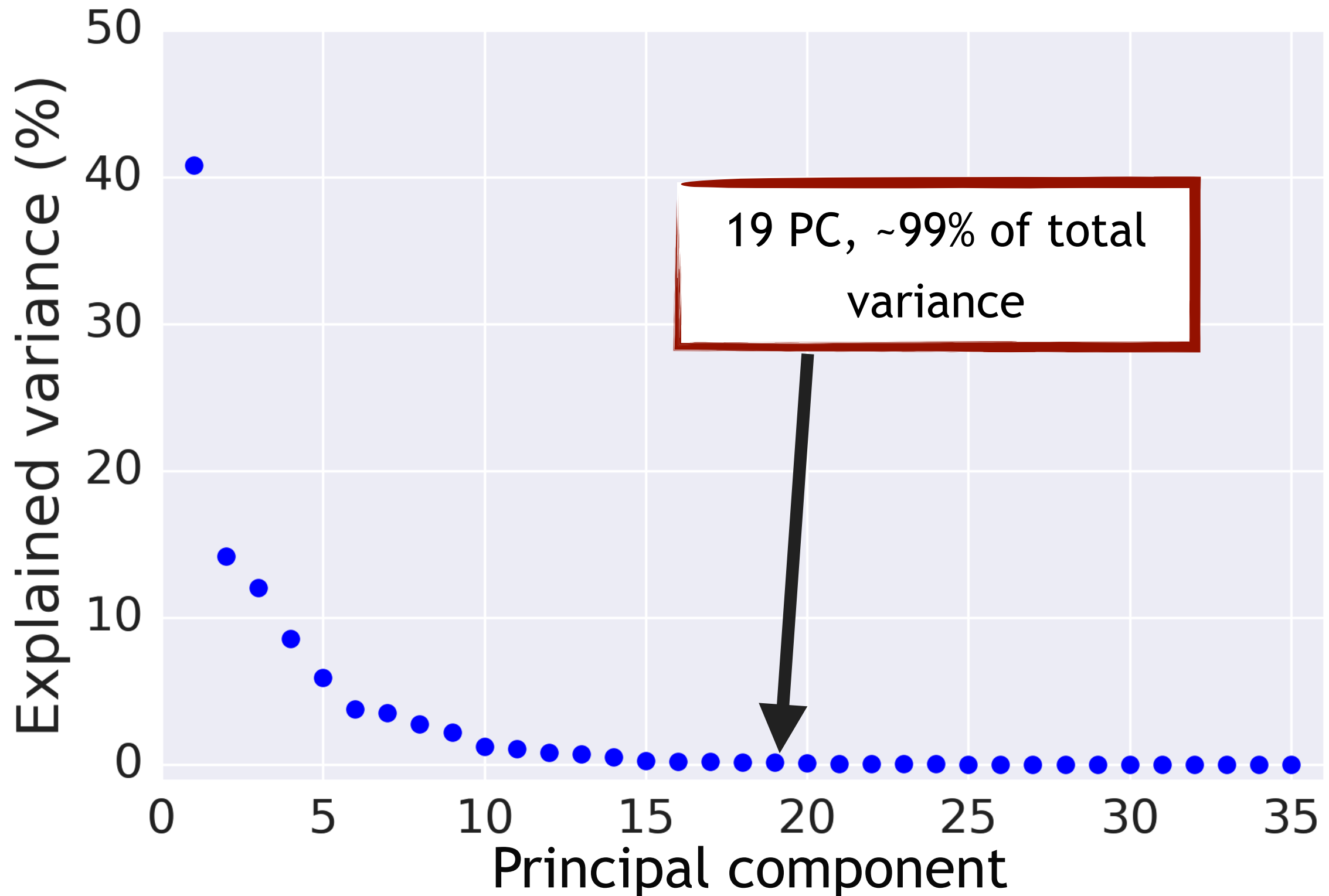
Reduce dimensionality before performing clustering

Average acc. area (μ_{Acc})	Max. stream order (Max_{ShrOrd})	length, w=slope ($\mu_{SPL_{w=S}}$)	unweighted (G_{uw})	w=slope ($W_{w=S}$)
Average width (μ_W)	Average sinuosity (μ_S)	Average in-degree, w=width ($\mu_{D_{w=W}}$)	Spectral gap, w=1/length ($G_{w=\frac{1}{L}}$)	Global efficiency (G_{eff})
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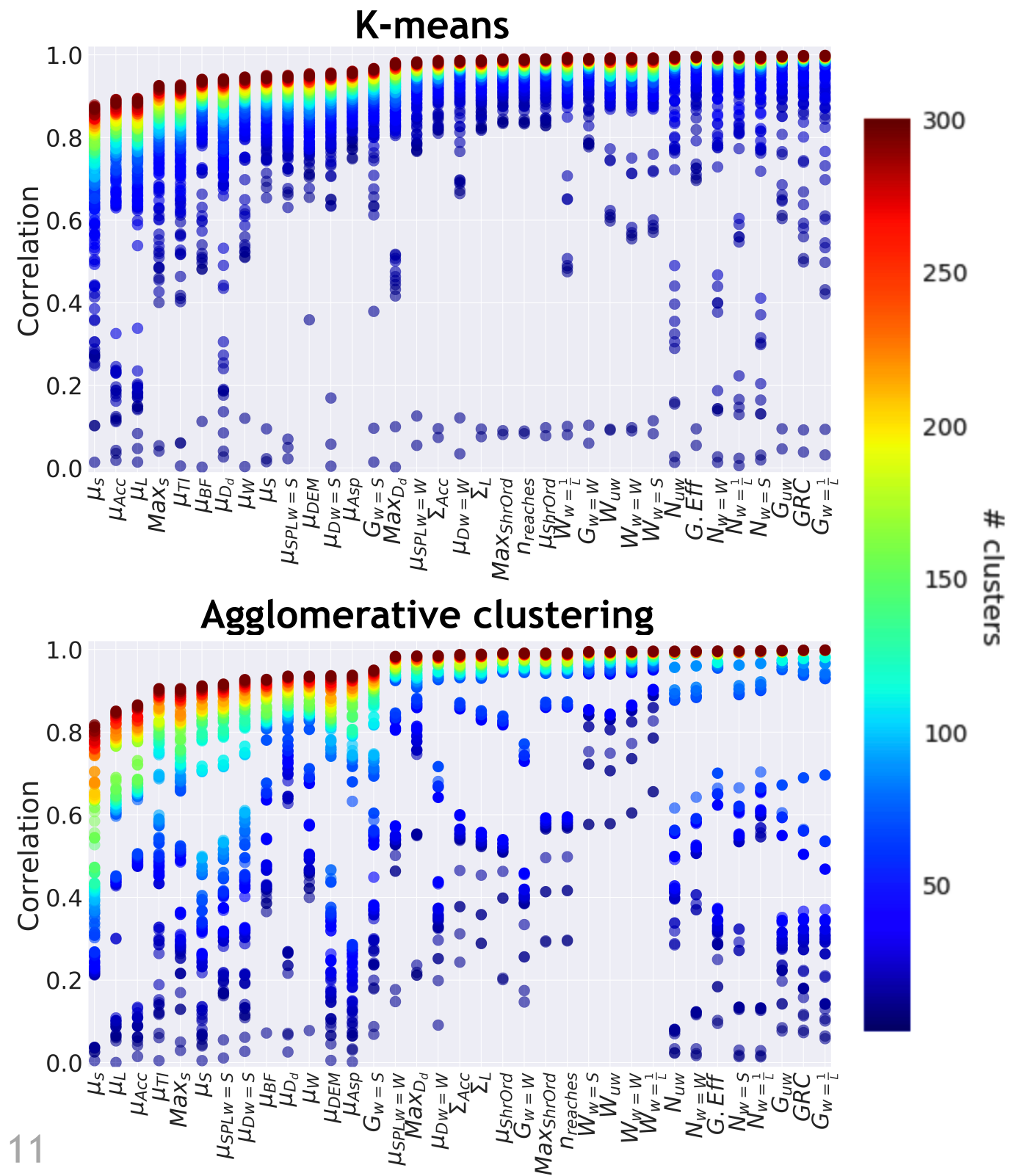
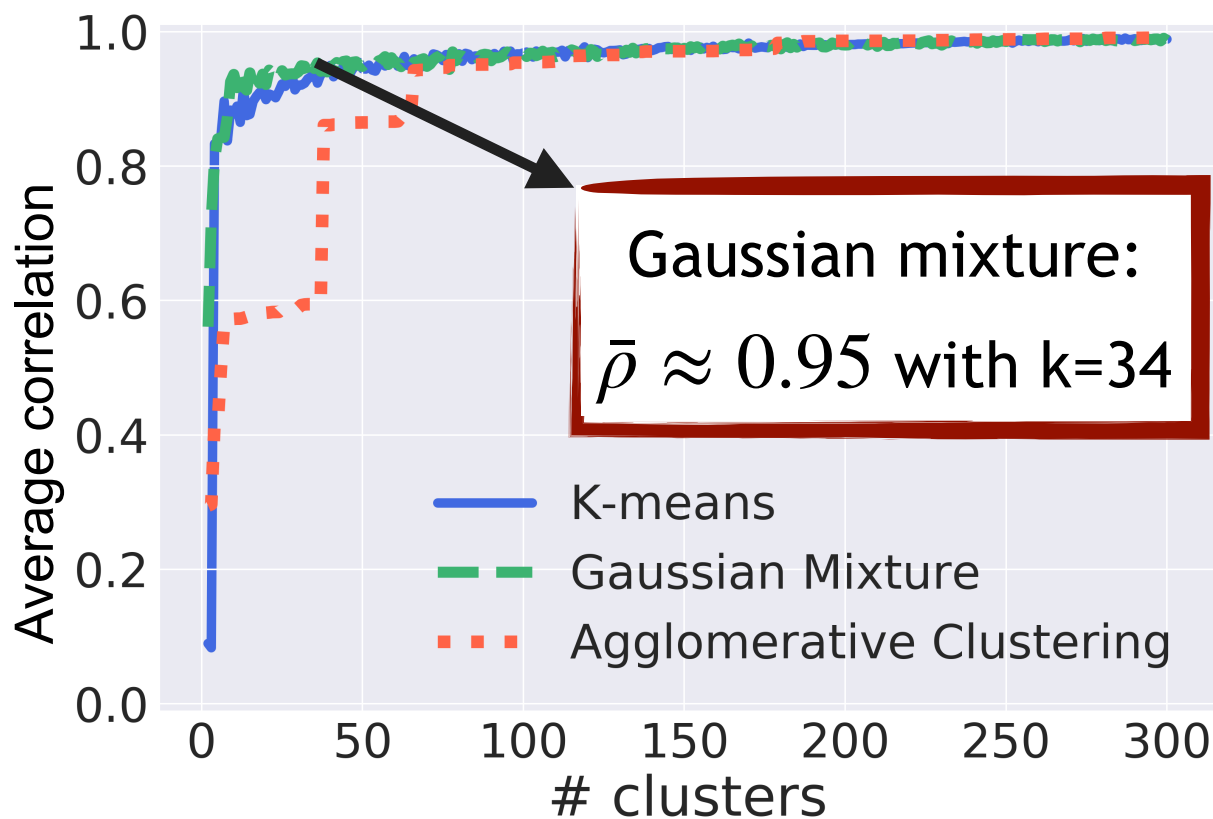
Stage 2: Clustering topologies

2.2. PCA for 85% threshold (~1,200 subnetworks)



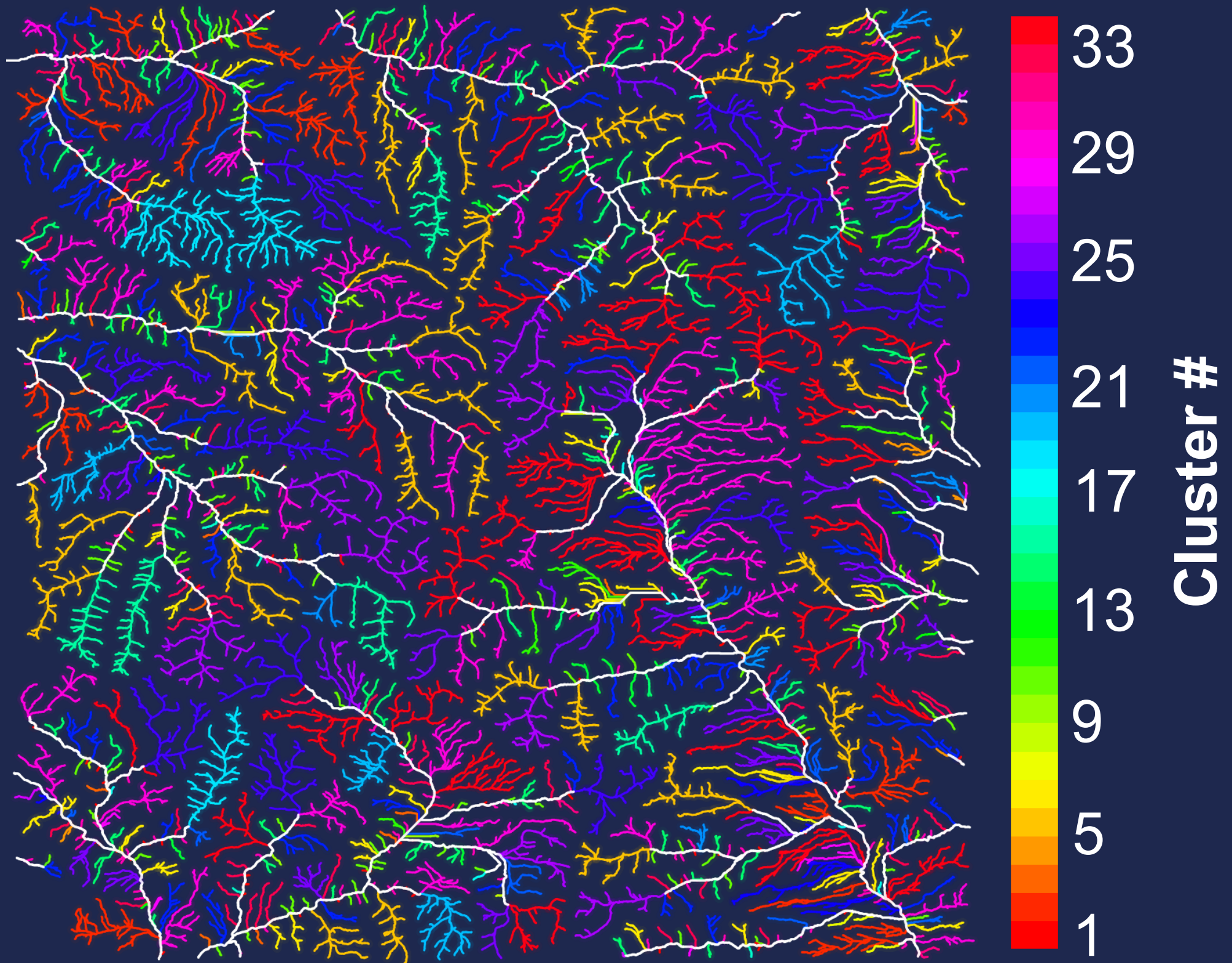
Stage 2: Clustering topologies

2.3. Selection: clustering algorithm and number of clusters



Stage 2: Clustering topologies

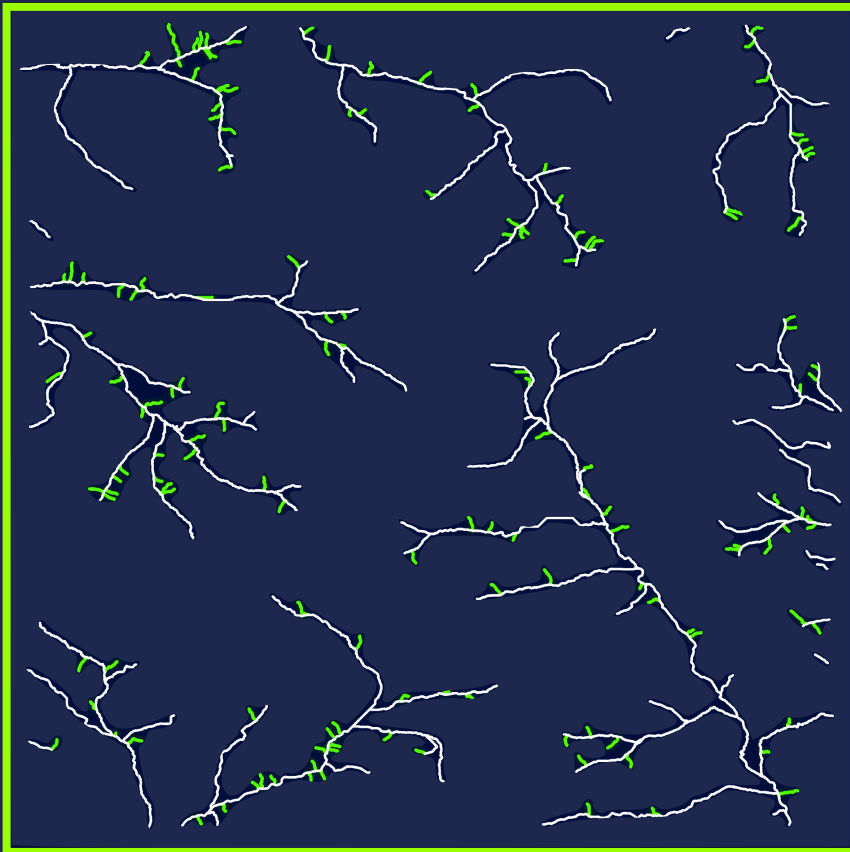
2.4. Clustering



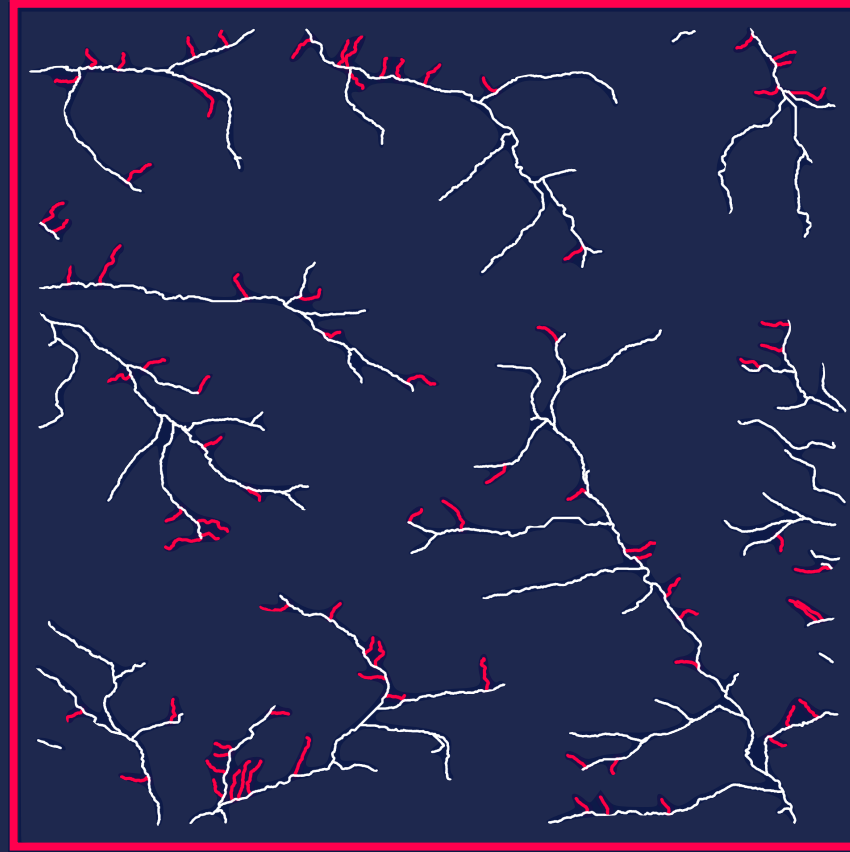
Stage 2: Clustering topologies

2.4. Clustering: First-order streams and simple topologies

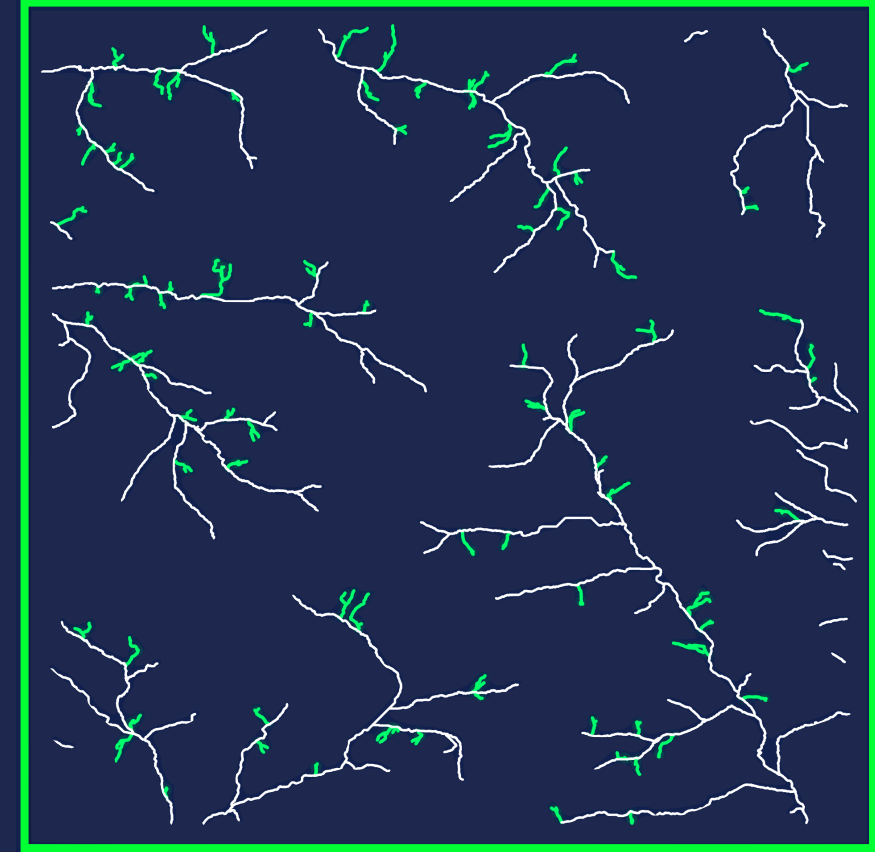
Cluster 10



Cluster 32



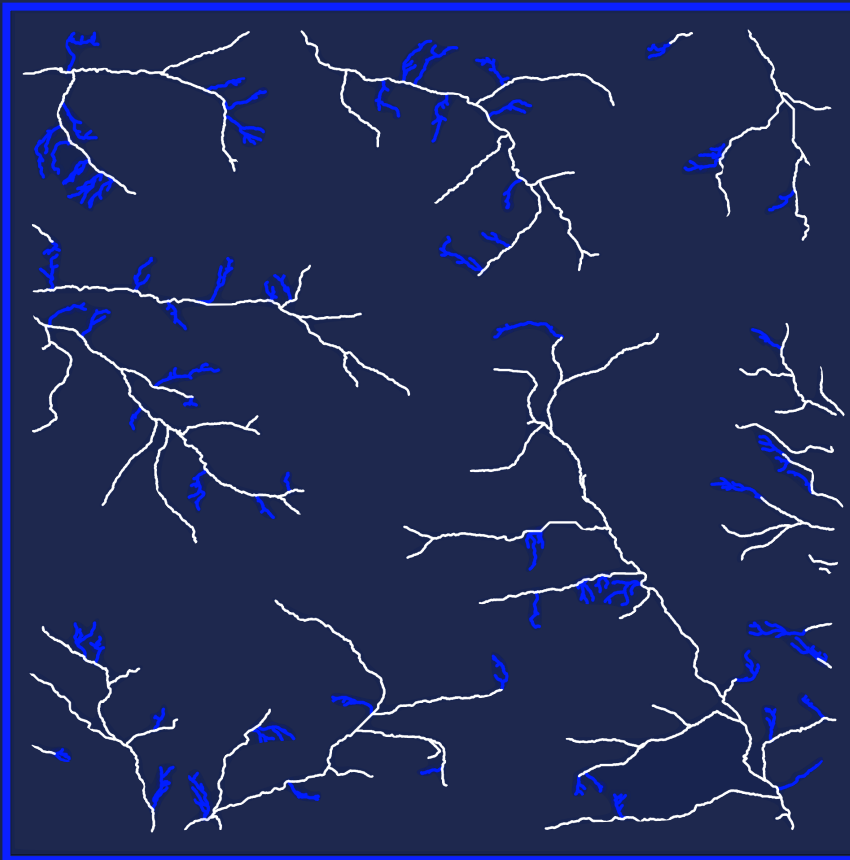
Cluster 14



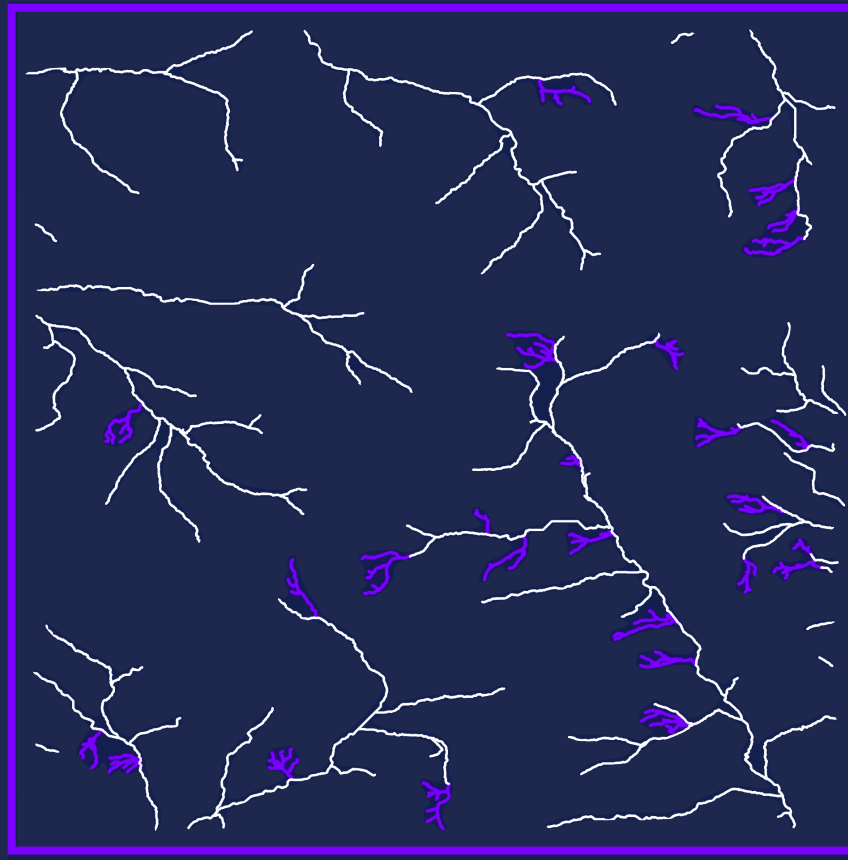
Stage 2: Clustering topologies

2.4. Clustering: Intermediate complexity structures

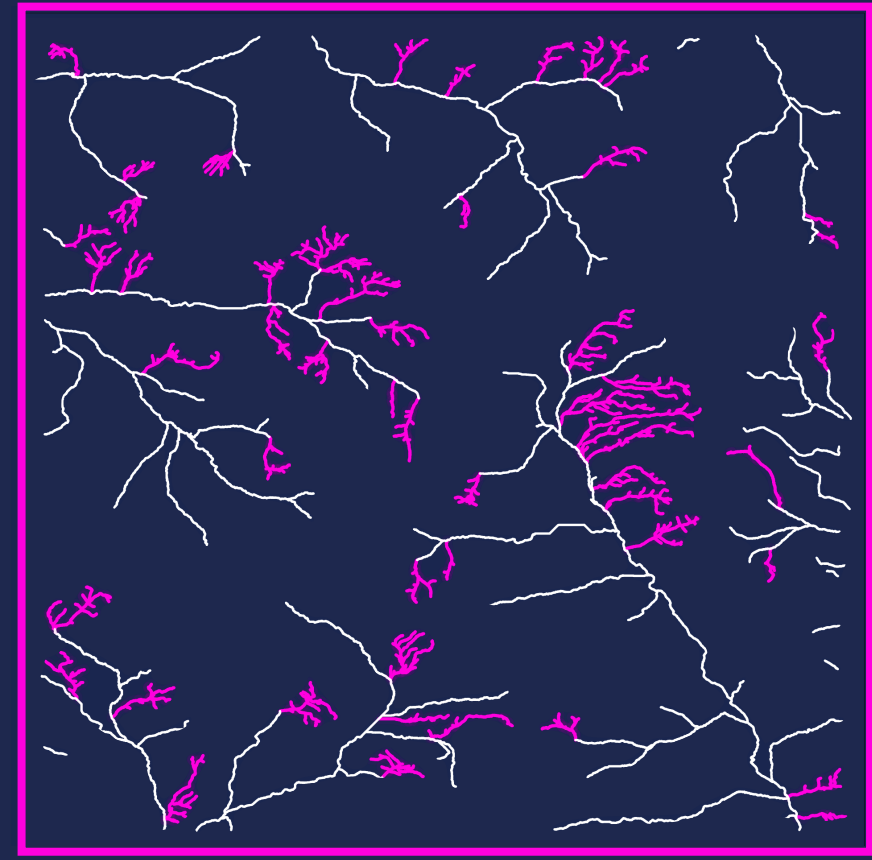
Cluster 22



Cluster 25

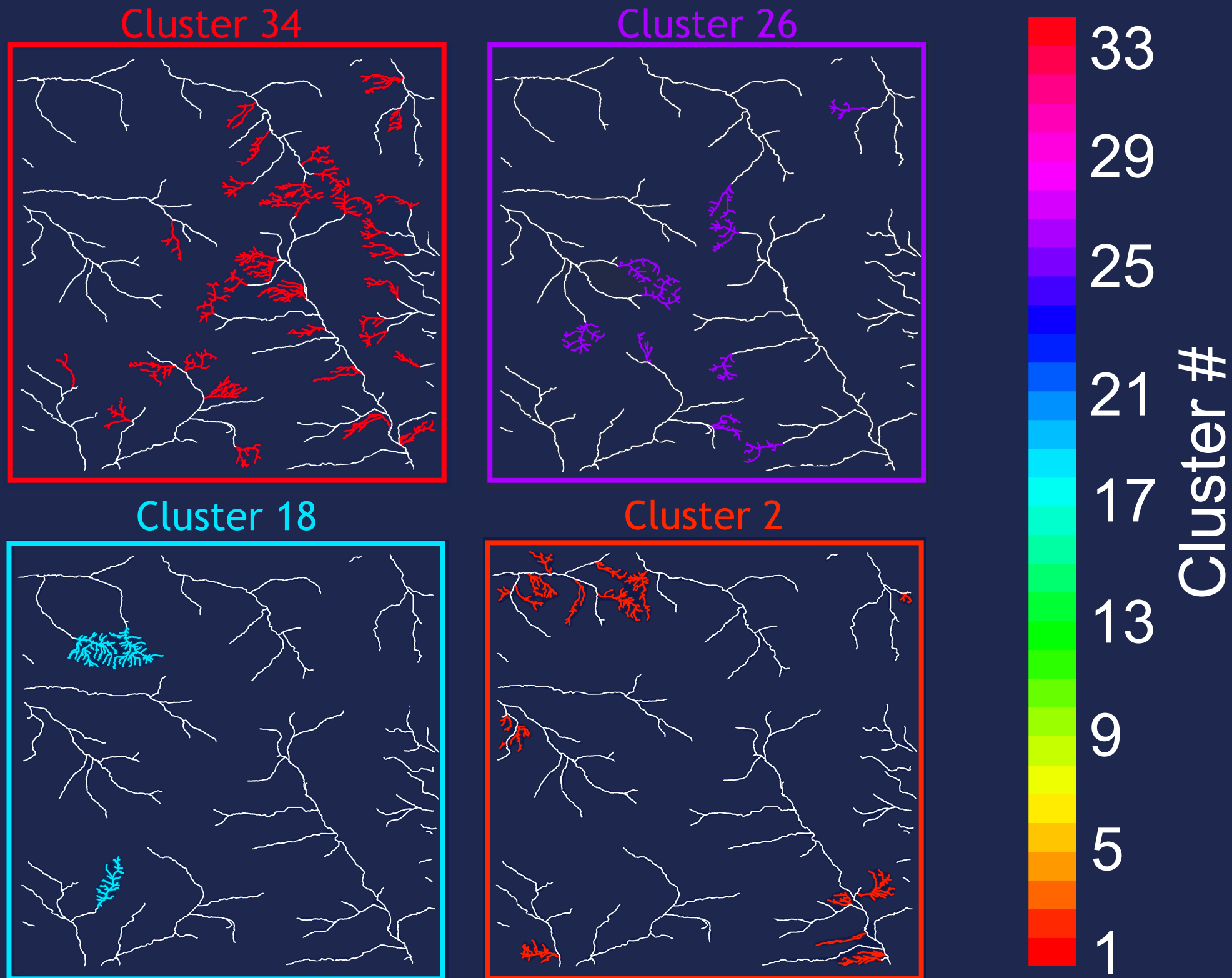


Cluster 29



Stage 2: Clustering topologies

2.4. Clustering: Highly complex structures



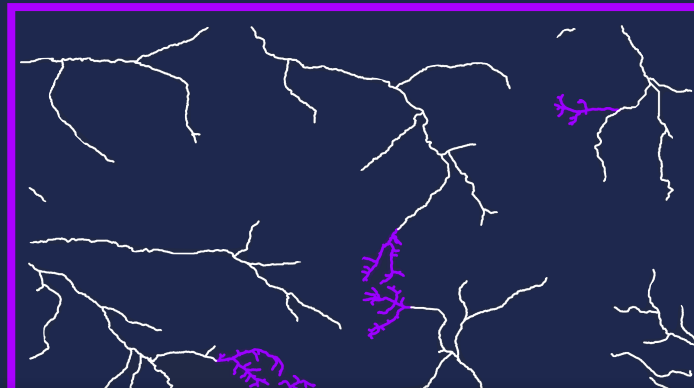
Stage 2: Clustering topologies

2.4. Clustering: Highly complex structures

Cluster 34

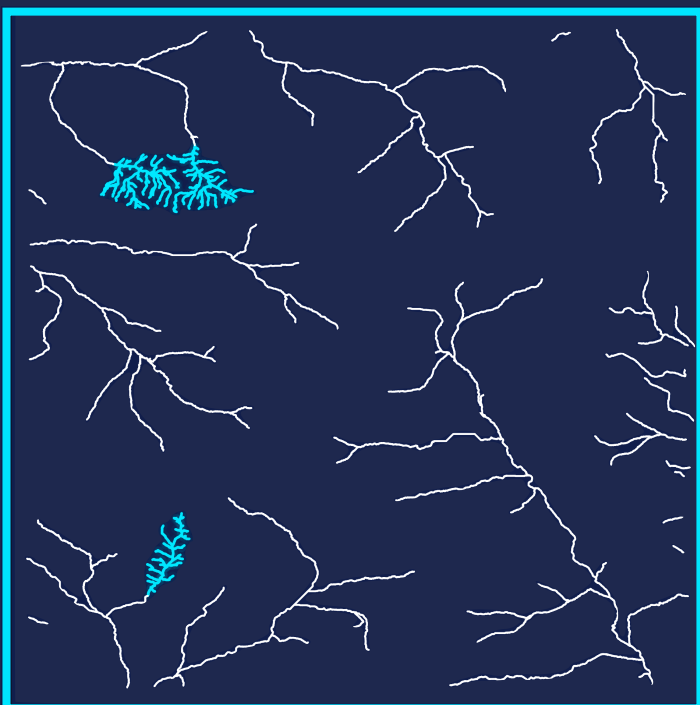


Cluster 26

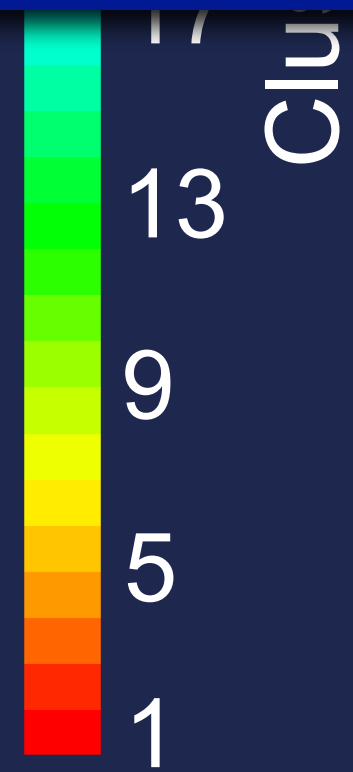
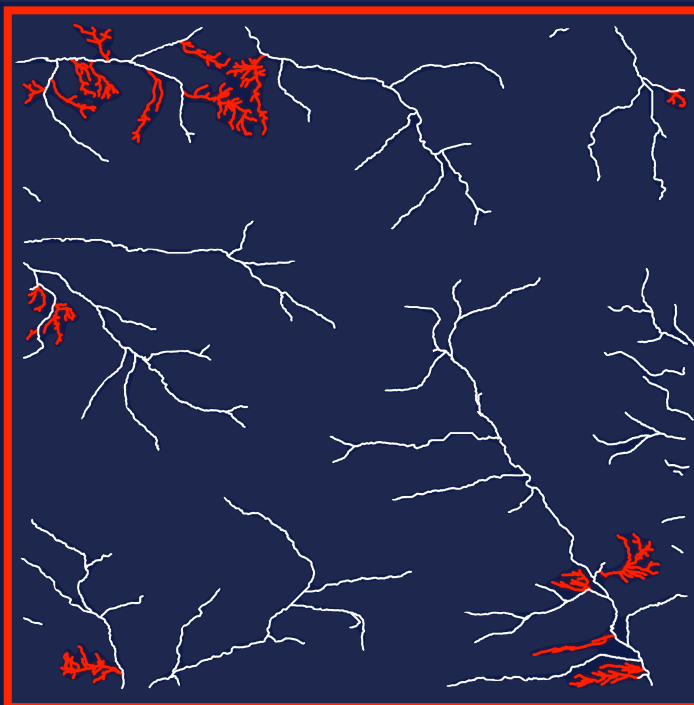


It works!

Cluster 18



Cluster 2



Final Thoughts and Future Directions

- Cluster the river channel structure over sets of interconnected reaches (i.e., topologies): **Possible!**
- Some questions remain:
 1. Influence of different covariates on the obtained clustering + weights used within the clustering.
 2. Are the selected topological metrics enough to characterize the trees on all scales? (i.e., complex vs. simple networks).
 3. Characteristic topology + 2-way coupling.
- Quantify computational saving derived from applying a topological clustering vs. “fully distributed” routing solution.
- Preliminary results show that topological clustering is a feasible and promising alternative to implement within ESMs.

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