Dynamic Manifold Learning for Land Deformation Forecasting

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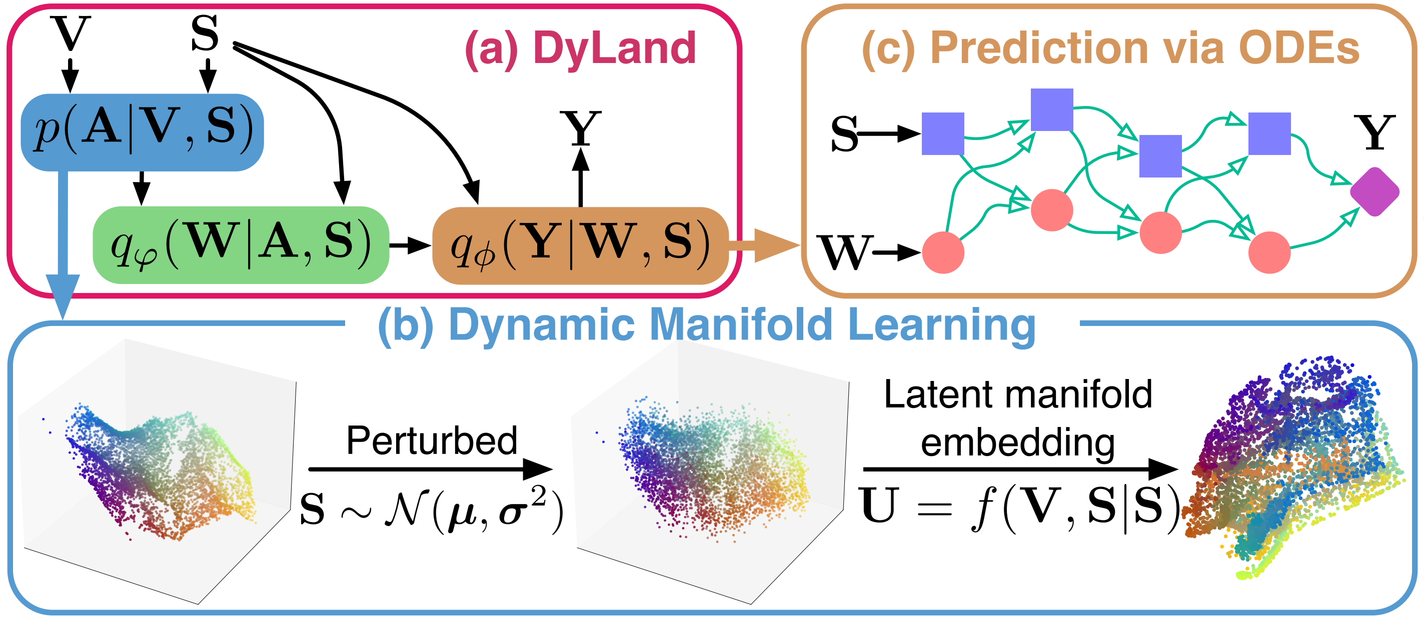
Framework of DyLand

Dynamic Manifold Learning with Normalizing Flows for **Land** deformation prediction

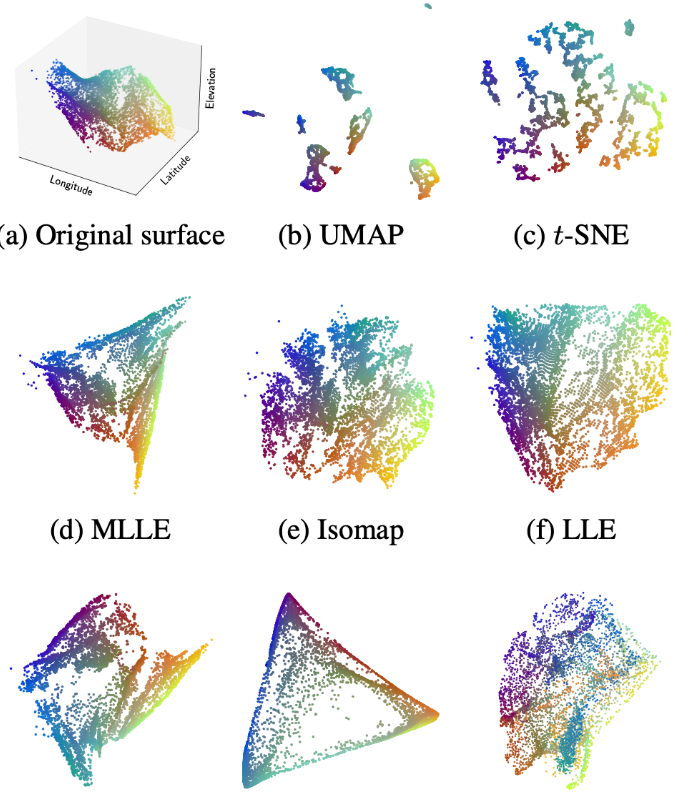
(a) The probabilistic learning of DyLand.

(b) The dynamic manifold learning. $\longrightarrow$ $\log p(\mathbf{v}_i'|\mathbf{s}_i^{\tau}) = \log p(\mathbf{u}_i^{\tau}) - \log\left|\det \dfrac{\partial f^{-1}(\mathbf{u}_i^{\tau}|\mathbf{s}_i^{\tau})}{\partial \mathbf{u}_i^{\tau}}\right|$

(c) The surface deformation prediction with ODEs. $\longrightarrow$ $\begin{bmatrix}\mathbf{S}^{t_1}\\ \mathbf{W}^{t_1}\end{bmatrix} = \begin{bmatrix}\mathbf{S}^{t_0}\\ \mathbf{W}^{t_0}\end{bmatrix} + \int_{t_0}^{t_1} g\left(\begin{bmatrix}\mathbf{S}^{t}\\ \mathbf{W}^{t}\end{bmatrix}, t\right) dt$



$\mathbf{V}$: Locations $\mathbf{S}$: Deformations $\mathbf{A}$: Adjacency matrix $\mathbf{Y}$: Predictions
$\mathbf{W}$: Spatio-temporal embeddings $\mathbf{U}$: Manifold embeddings



(a) Original surface (b) UMAP (c) *t*-SNE
(d) MLLE (e) Isomap (f) LLE
(g) LTSA (h) WLLE (i) DyLand

Contributions

We explicitly explore the temporal dynamics of land surface and topological dependencies between monitored locations to study the land deformation prediction.

We propose a flow-based generative models method for density estimation on a dynamic manifold.

We consider the temporal deformation and spatio-temporal representation learning as a dynamic system, and introduce a method based on neural ordinary differentiable equations (NODE).

Visualizations and Comparisons