Sea Level Rise Prediction with Deep Learning Project Proposal

1) Overview

Rising sea levels pose a critical threat to coastal communities, ecosystems, and infrastructure worldwide. Accurate regional forecasting of sea level rise (SLR) is essential for adaptive planning, yet traditional models often lack the spatial and temporal resolution required for actionable insights. This project proposes a deep learning framework leveraging transformer networks to predict SLR by integrating spatiotemporal data from ocean currents, satellite altimetry, and coastal topography. Transformers, with their ability to model long-range dependencies and hierarchical patterns, are well-suited to handle the complex interdependencies between these datasets. The model will synthesize high-resolution outputs to forecast regional SLR trends, enabling policymakers and stakeholders to prioritize mitigation efforts in vulnerable areas.

The approach combines physics-informed machine learning with empirical data analysis. Ocean current measurements provide dynamic flow patterns influencing heat distribution and sea surface elevation, while satellite altimetry offers precise, large-scale elevation data. Coastal topography maps contextualize local vulnerability by identifying low-lying regions. By training a transformer on these multimodal inputs, the model can capture nonlinear interactions between drivers of SLR, such as thermal expansion and ice sheet melt. The output will include probabilistic forecasts at sub-regional scales, improving upon global averages that obscure localized risks. This project bridges gaps in existing SLR modeling by prioritizing scalability, resolution, and interpretability.

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2) Data Section

Sources

1. **Ocean Current Measurements**:

- **Source**: National Oceanic and Atmospheric Administration (NOAA) Global Drifter Program and Ocean Observatories Initiative (OOI).

- **Format**: NetCDF files containing velocity vectors (u, v components) at 0.25° spatial resolution and daily temporal resolution.

- **Access**: Publicly available via NOAA’s Climate Data Record (CDR) portal and the OOI Data Portal.

2. **Satellite Altimetry Data**:

- **Source**: NASA’s Jason-3 and Sentinel-6 missions, and the European Space Agency’s CryoSat-2.

- **Format**: GeoTIFF and NetCDF files with sea surface height (SSH) anomalies at 30–100 km spatial resolution and 10-day revisit cycles.

- **Access**: Through NASA’s Physical Oceanography Distributed Active Archive Center (PODAAC) and ESA’s Copernicus Open Access Hub.

3. **Coastal Topography Maps**:

- **Source**: U.S. Geological Survey (USGS) Coastal and Marine Geology Program and the ETOPO1 Global Relief Model.

- **Format**: Shapefiles and GeoTIFFs with bathymetric/topographic data at 2–30 arcsecond resolution (approx. 60–1 km).

- **Access**: Available via USGS Earth Explorer and NOAA's Digital Elevation Model (DEM) repository.

Data Integration

- **Temporal Alignment**: All datasets will be interpolated to a common 10-day time step using cubic spline interpolation.

- **Spatial Harmonization**: ETOPO1 will serve as the baseline geographic reference, with regridding of other datasets to match its 1-minute resolution via bilinear interpolation.

- **Preprocessing**: Missing values will be imputed using k-nearest neighbors, and feature scaling will normalize inputs for the transformer architecture.

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3) Feasibility Discussion

The technical feasibility of this project hinges on three pillars: **data quality**, **algorithmic capacity**, and **computational resources**. First, the availability of high-resolution, publicly accessible datasets from NOAA, NASA, and USGS ensures robust training data. However, challenges arise in harmonizing disparate spatial and temporal resolutions, which requires rigorous preprocessing. Second, transformers have demonstrated exceptional performance in spatiotemporal forecasting tasks, such as weather prediction and traffic flow modeling. Their self-attention mechanisms can effectively capture long-term dependencies between oceanographic variables, though training stability may require careful hyperparameter tuning and regularization. Third, the computational demands of transformer networks necessitate access to GPU/TPU clusters (e.g., AWS EC2 P4 instances or Google Cloud TPUs). While feasible with cloud infrastructure, costs for large-scale training and inference must be managed through efficient model quantization and pruning techniques.

A key feasibility risk is the potential for overfitting due to the high dimensionality of spatiotemporal data. Mitigation strategies include cross-validation with holdout regions, incorporation of physical constraints (e.g., mass conservation in ocean currents), and adversarial training to enforce consistency between predicted and observed SLR patterns. Additionally, collaboration with domain experts (e.g., oceanographers) will ensure the model aligns with established physical principles, enhancing interpretability and trustworthiness.

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4) Suggested Next Steps and Extensions

1. **Initial Model Development**:

- Design a transformer architecture with parallel encoders for each data modality (ocean currents, altimetry, topography) and a cross-attention fusion layer.

- Validate the model using historical SLR data from the IPCC AR6 dataset, focusing on regions with documented acceleration in rise rates (e.g., the Gulf Coast and Southeast Asia).

2. **Uncertainty Quantification**:

- Integrate Bayesian neural networks or Monte Carlo dropout to quantify predictive uncertainty, enabling probabilistic SLR forecasts (e.g., 95% confidence intervals).

- Conduct sensitivity analysis to identify which input variables (e.g., temperature trends vs. ice melt) dominate predictive errors in different regions.

3. **Policy and Infrastructure Applications**:

- Partner with municipal planning departments to test model outputs in flood risk mapping and zoning policy simulations.

- Develop a web-based dashboard (e.g., using Plotly or GRASS GIS) to visualize SLR projections alongside socioeconomic vulnerability indices.

4. **Long-Term Extensions**:

- Incorporate real-time data streams from emerging Earth observation satellites (e.g., NASA's NISAR) for dynamic SLR monitoring.

- Expand the model to include ice sheet dynamics and groundwater extraction impacts, creating a holistic SLR forecasting system.