Spatio-Temporal Machine Learning for Ecology and Crisis Management

The exponential growth of spatio-temporal data from satellites and digital communications presents a great opportunity to address planetary-scale challenges. However, standard deep learning models, trained on conventional datasets, are often suboptimal for the specialized, context-dense, and scarce data that characterize domains like ecology and crisis management. This difference creates a significant bottleneck, limiting the conversion of raw data into actionable intelligence.

This thesis argues that effectively monitoring our planet requires a unified framework capable of handling systems in two distinct but interconnected states: long-term, gradual evolution (Ecology) and short-term, acute shocks (Crisis Management). Challenging the current trend of relying on monolithic, general-purpose models, this work demonstrates that a portfolio of targeted, data-efficient, and interpretable architectures provides a more robust, scalable, and trustworthy solution.

To achieve this, the thesis introduces a suite of novel machine learning models and foundational, public datasets designed to tackle the core challenges of specialized data. The contributions include: 1) data-efficient methods that achieve state-of-the-art performance on scarce or sparsely labeled data; 2) architectures that synthesize dynamic, multi-modal data streams into a coherent operational picture; and 3) explainable models that build trust with domain experts.

The proposed models demonstrate state-of-the-art performance across all tasks. In ecological monitoring, the proposed architecture for cross-modal land use classification achieved 54% greater accuracy than existing methods. In crisis management, the real-time tracker provides a significant computational advantage, operating at a constant cost regardless of data scale (in contrast to the linear complexity of competitors), while maintaining state-of-the-art accuracy. The creation of these four new benchmark datasets was essential to both achieving and validating these performance gains.

Ultimately, this thesis establishes that specialized, efficient systems are essential for unlocking the full potential of complex spatio-temporal data. The developed models and datasets offer immediate practical benefits for ecologists and crisis managers, enhancing decision-making in precision agriculture, water management, and disaster response to help build a more resilient and sustainable future.