Integration of spatial-temporal context in remote sensing image classification

MSc Thesis intermediate presentation

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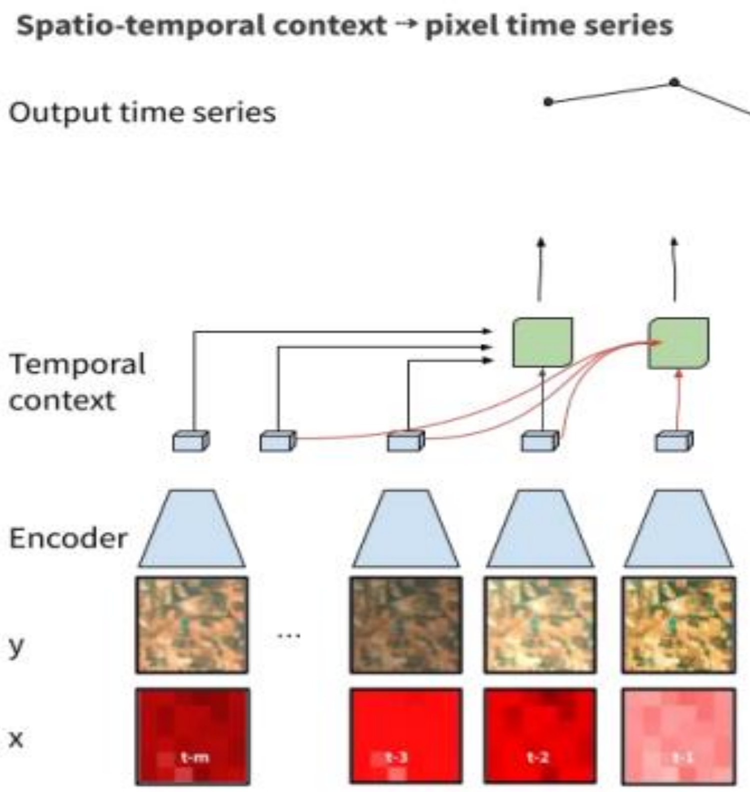
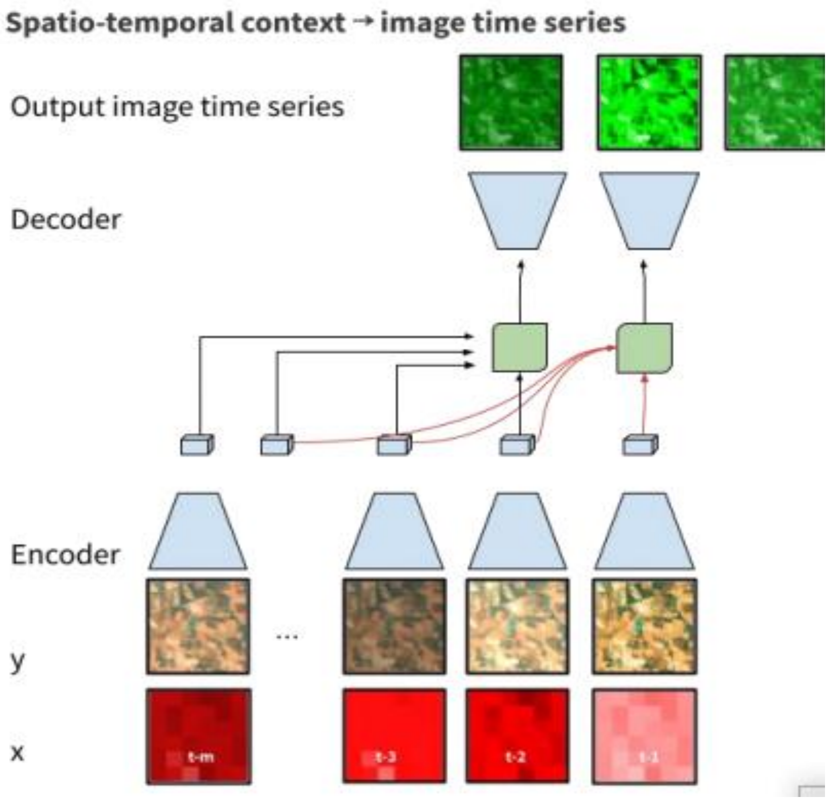
CONTENTS

1. INTRODUCTION

Problem:

Most machine learning methods analyze **pixel-by-pixel** and do not consider **the spatial context**, so there are limitations in analyzing large-scale satellite images.

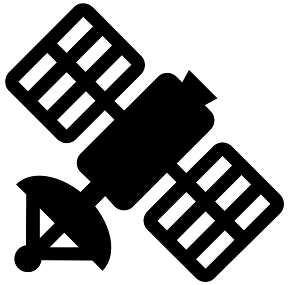


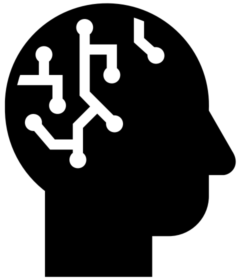


1. INTRODUCTION

Aim:

Exploring opportunities for **spatial-temporal** learning in remote sensing data analysis using **deep learning methods.**





Remote sensing (RS)

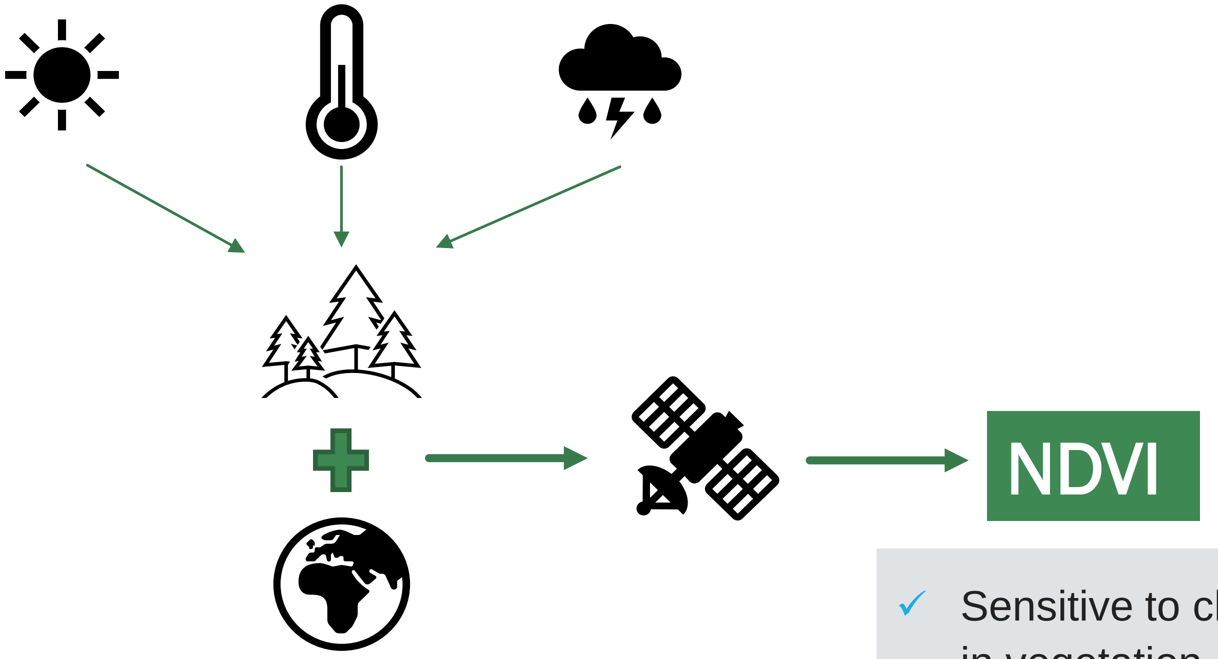
- Large-scale spatial imagery over long time scales

Deep learning method

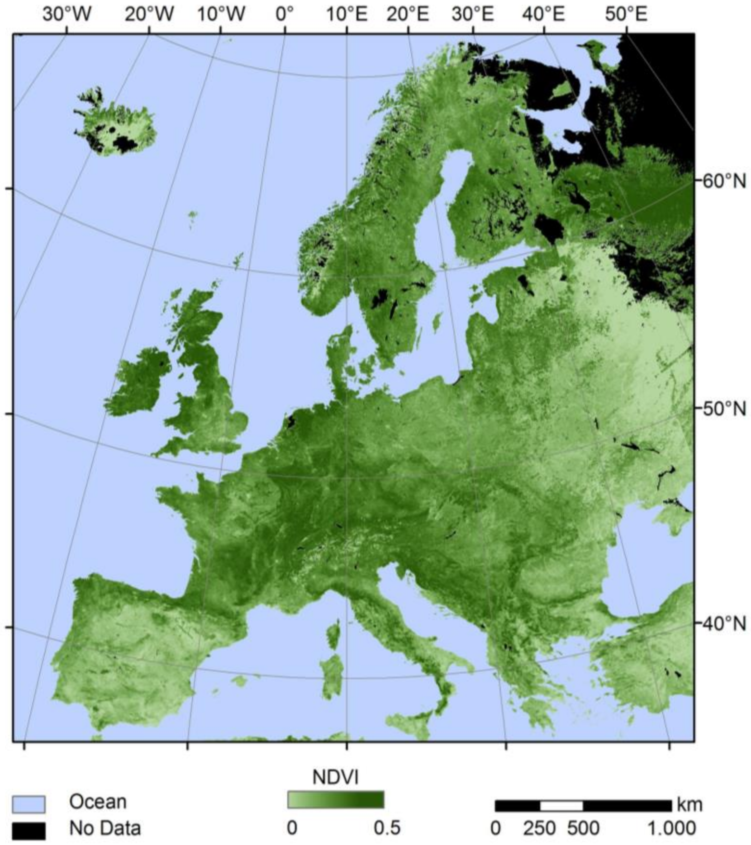
- Automatically learn complex patterns
- Achieve higher accuracy and better generalization on complex datasets

2. LITERATURE REVIEW

2.1 REMOTE SENSING & NDVI



- ✓ Sensitive to changes in vegetation
- ✓ Data easy access



Europe map of NDVI from August 1990 [1]

2. LITERATURE REVIEW
2.2 DEEP LEARNING MODEL

Deep learning

- DL can automatically learn complex patterns and features from large amounts of data.
- DL can achieve higher accuracy and better generalization for RS data as it capture both spatial and temporal dependencies.
- Common DL methods: CNN, RNN, LSTM.

Deep learning application in RS

- **Image Classification.**

E.g.: CNN Classifies RS Images into different land cover and land use classes (index: NDVI).

- **Object detection.**

E.g.: deforestation, urbanization, and agricultural expansion.

- **Environmental and climate monitoring.**

E.g.: Monitoring wildfires, floods, droughts.

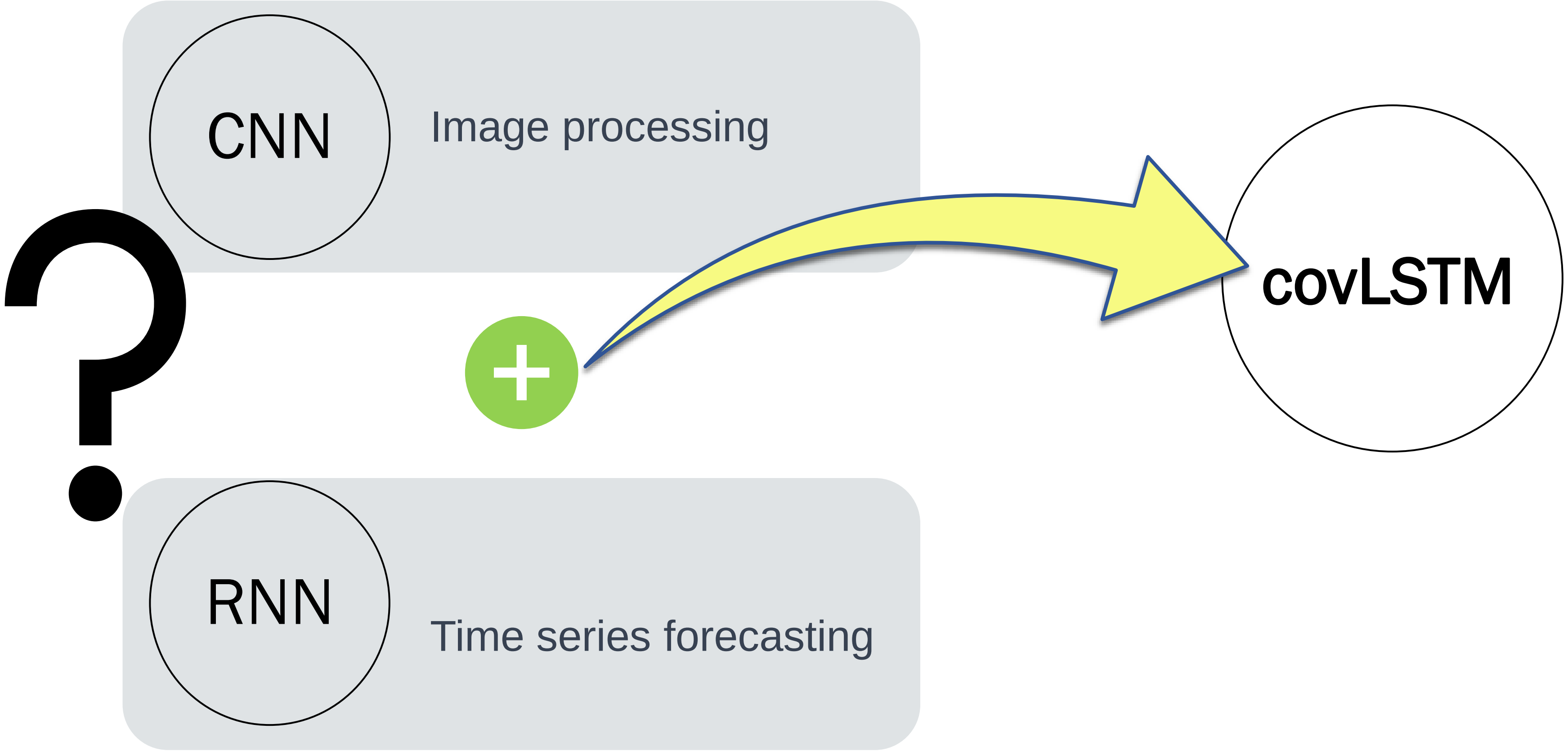
2. LITERATURE REVIEW

2.2 DEEP LEARNING MODEL

CNN	• Good at process and **analyze image data**. Capture complex relationships between pixels and their surroundings.	• Not good at **capturing time dependencies**.
RNN	• Good for **time series forecasting**, good at capturing time dependencies between observations.	• **Long-term dependencies** may not be captured. • Not good at **capturing spatial features** in image data.
LSTM	• A type of RNN, ideal for **time series forecasting,** can capture long-term dependency.	• Requires a large amount of training data and is computationally expensive. • Not good at **capturing spatial features** in image data.

2. LITERATURE REVIEW

2.2 DEEP LEARNING MODEL



- Combination of CNN and LSTM models.
- Learn the spatial and temporal characteristics of the data, **particularly suitable for analyzing spatiotemporal data.**

2. LITERATURE REVIEW
2.3 DATA SOURCES AND PREPROCESSING

EarthNet2021

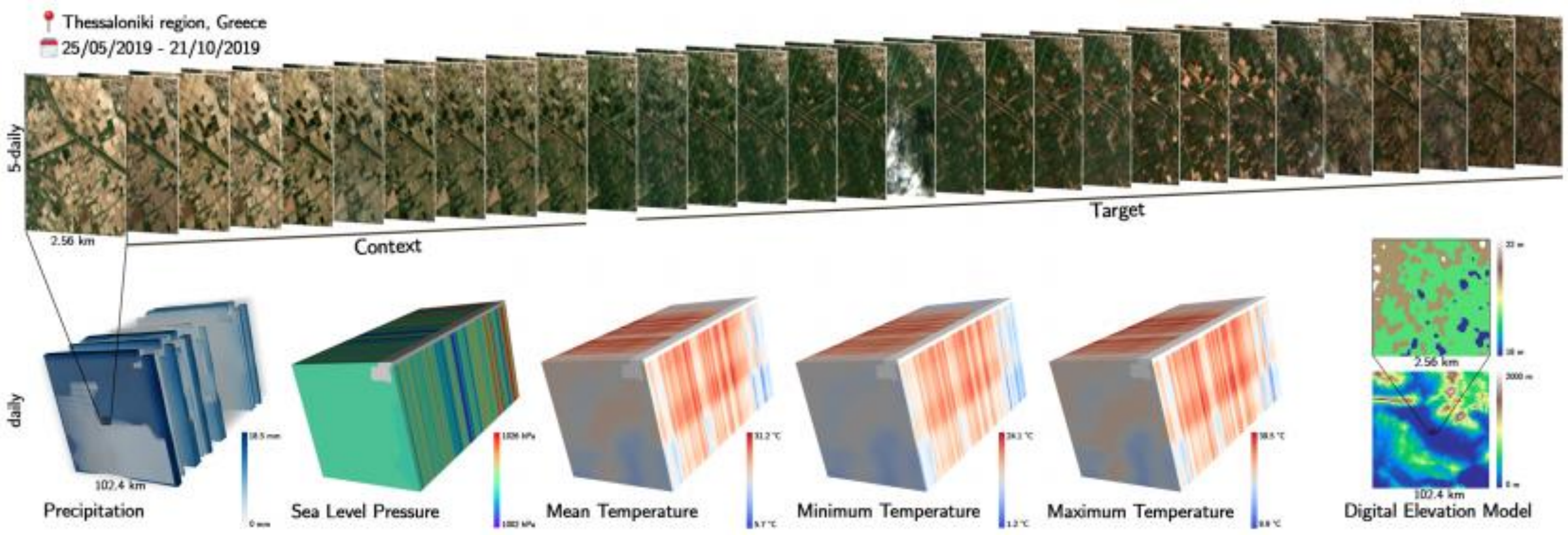


Figure 1: Overview visualization of one of the over 32000 samples in EarthNet2021.

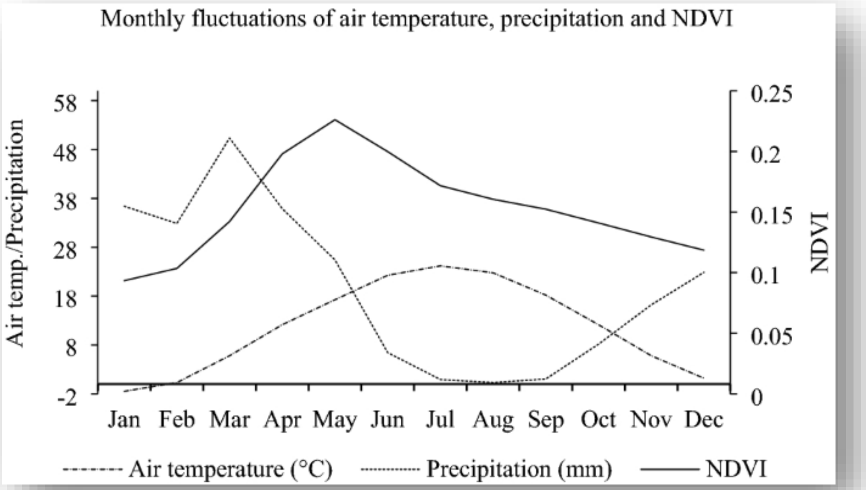
- A large data set for training deep neural networks [2].
- Contains 20 m resolution **Sentinel-2 satellite imagery.**
- Contain **climate variables**: precipitation, sea-level pressure and temperature.
- Contain digital elevation model **(DEM)**.

2. LITERATURE REVIEW

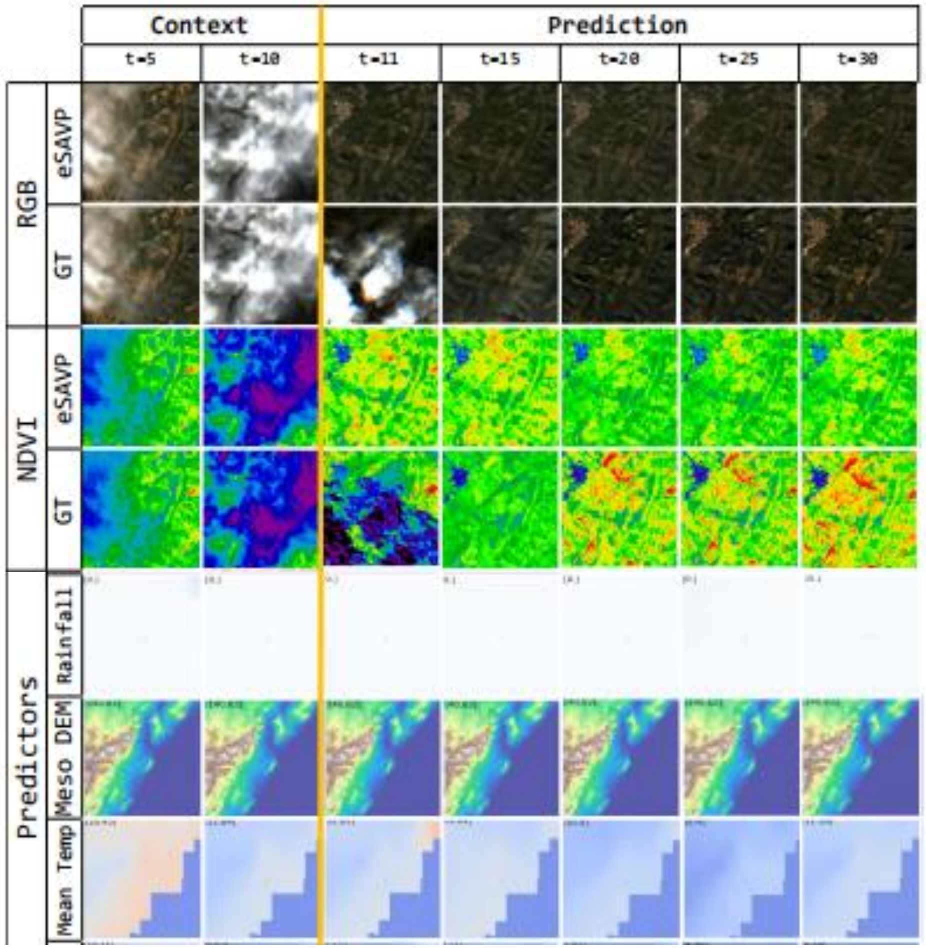
2.3 DATA SOURCES AND PREPROCESSING

Data preprocessing – Earthnet 2021

- Image Registration.
- Remove clouds and shadows.
- Feature extraction: temperature, rainfall, DEM.



Monthly fluctuations of air temperature, precipitation, and NDVI in time period of 1987–2016 in Iran [3]



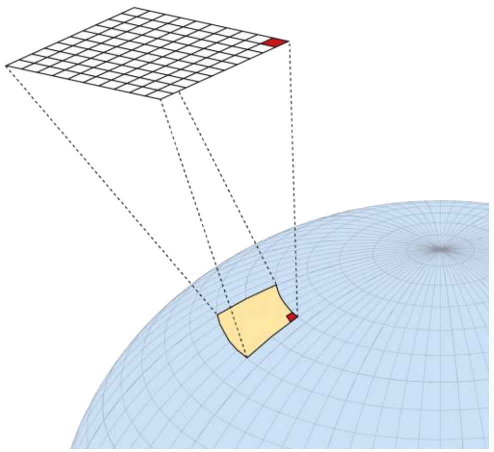
The represent of NDVI and the weather variables on RS image [2]

3. THESIS STRUCTURE

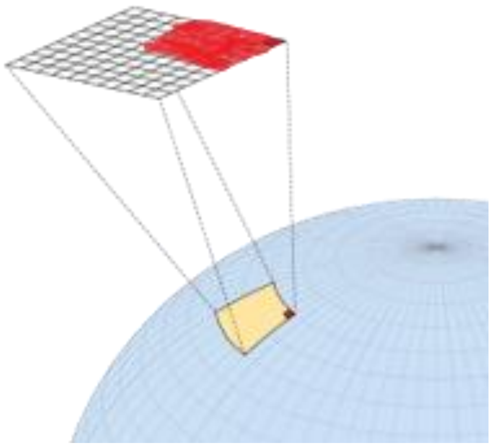
3.1 RESEARCH QUESTION

Research question

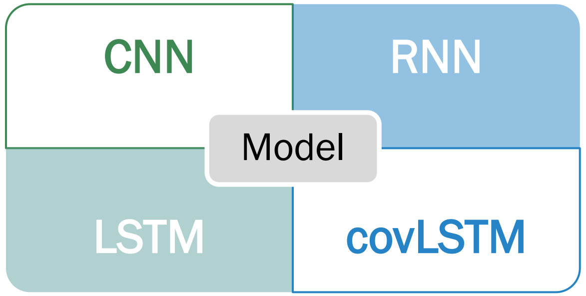
- Can we use **deep learning models** to **predict the NDVI** of a pixel on a remote sensing image based on known NDVI and related weather variables? And how much does the model‘s predictive ability change when **spatially expanding the simulated pixels range**?



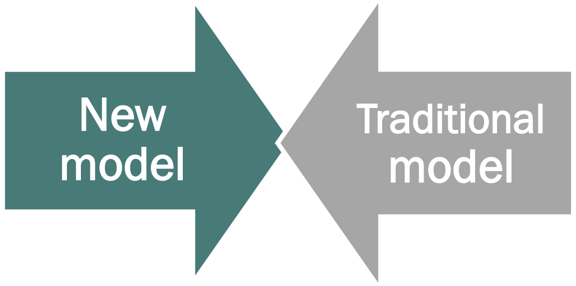
Single pixel



More pixels



Deep learning model



Predict result compare

3. THESIS STRUCTURE

3.2 METHODOLOGY

Data source

- NDVI
- Mean Temperature
- Rainfall
- EU-DEM

Data preprocessing

- NDVI is calculated from wavelength
- Keep all variables in same time steps
- Missing value filling
- Normalization
- Split into training, validation, and testing sets

Deep learning models

- CNN
- RNN
- covLSTM

Model evaluation

- Mean Absolute Error (MAE)
- Root Mean Squared Error (RMSE)
- Correlation coefficient (r)

3. THESIS STRUCTURE
3.3 EXPECTED OUTCOME

Expect result:

- ❑ Single pixel → RNN model
- ❑ Pixel and surrounding pixels → covLSTM model
- ❑ More pixels and weather variables may improve forecast accuracy!

Applications:

- ✓ Crop yield forecasting,
- ✓ land use mapping,
- ✓ Ecosystem monitoring yield

4. FUTURE WORK

Literature overview

Thesis structure

Data download and preprocessing

Deep learning model selection

By 24th Feb 2023

Train the model

Develop and evaluate the model

Write the thesis

June exam period

8th June

Jan. - Feb. 2023	Mar. – May 2022	May – Jun. 2022
Literature overview Initialize model	Development and Evaluation of the model	Writing Thesis

REFERENCE

- [1] https://www.dlr.de/eoc/en/desktopdefault.aspx/tabid-9142/19518_read-45426/
- [2] Christian Requena-Mesa, Vitus Benson, Markus Reichstein, Jakob Runge and Joachim Denzler. EarthNet2021: A large-scale dataset and challenge for Earth surface forecasting as a guided video prediction task. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) Workshops, 2021.
- [3] Bagherzadeh, A., Hoseini, A.V. & Totmaj, L.H. The effects of climate change on normalized difference vegetation index (NDVI) in the Northeast of Iran. Model. Earth Syst. Environ. 6, 671–683 (2020).
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