AI4EO

Special Topics in Applications (AIL861)
Artificial Intelligence for Earth Observation
Lecture 20

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Further challenge in mapping debris-covered glaciers

Mapping of debris-covered glaciers in Alpine regions is still challenging due to many factors including similarity between debris and the adjacent bedrock, shadows cast from mountains (source: Glacier Mapping Based on Random Forest Algorithm: A Case Study over the Eastern Pamir)

Potential solutions

- ✔ Capturing texture and spatial context (CNN)
- ✔ Taking other inputs like thermal input (multi-sensory learning)
- ✔ Movement velocity features (time-series analysis, e.g., using LSTM)

Further challenge in mapping debris-covered glaciers

Detecting boundary of clean ice and debris-covered glacier facies is a challenging aspect.

(source: Glacier Facies Mapping Using a Machine-Learning Algorithm: The Parlung Zangbo Basin Case Study)

Potential solution

Edge-aware model learning.

(e.g., recall U-Net actual model proposed in 2015)

Glacier Change Detection

- ✔ Most glaciers keep moving slowly
- ✔ Even in absence of any change, the co-registration error may induce errors in change detection methods.
- ✔ Potential solution: recall our discussion on planetary change detection.

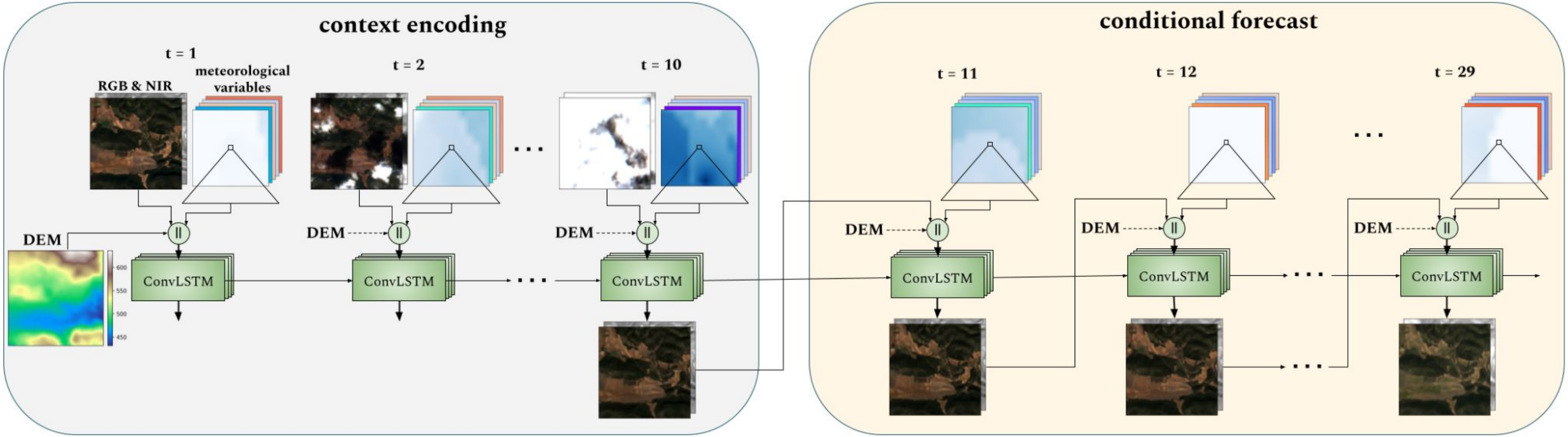
Weather Data for Earth Surface Forecasting

Problem

- Problem: Earth Surface Forecasting i.e. predicting future satellite imagery based on previous context frames, conditioned on a certain future weather scenario.
    - auxiliary information can also be used, e.g. elevation maps
    - can be framed as a guided video-prediction task

- Motivation:
    - Use seasonal forecasts for estimating the crop yield, drought risks and others
    - But only knowing these forecasts may not be enough because of many local factors (e.g. soil type, slope, water vicinity etc), whereas the satellite imagery captures some of them
        - additionally, the spatial resolution of seasonal forecasts can be too coarse
    - Once we have the predicted imagery, it can be used in many downstreams applications
    - Lots of data available for training since no labelling is needed

A Conv-LSTM based model



- Advantages:
  - exploits the temporal dimension using their recurrent inductive bias
  - by training frame by frame, the future predictions are explicitly constrained on the previous weather maps

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EarthNet2021 (Requena-Mesa et al., 2021)

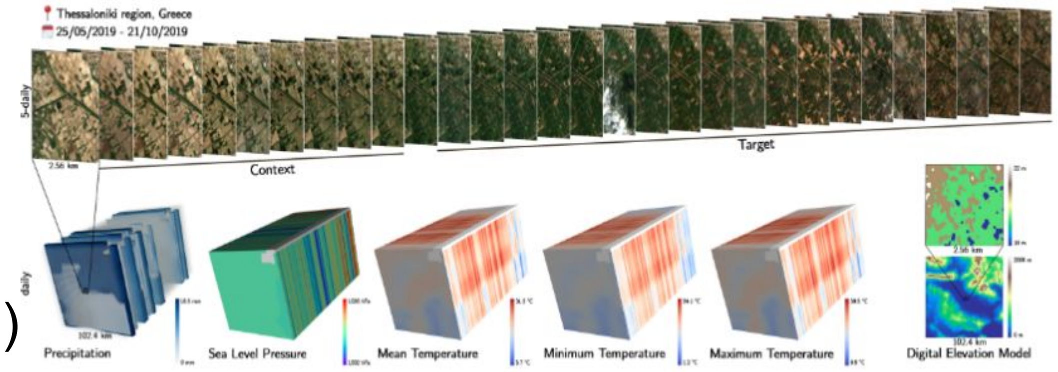


Figure 1: Overview visualization of one of the over 32000 samples in EarthNet2021.

Figure from (Requena-Mesa et al., 2021)

- relatively large dataset (~600Gb on disk, compressed)
- 32000 samples, each consisting of:
  - 30 frames from Sentinel-2
    - 5 days interval => a period of 150 days
    - 4 channels used: RGB + NIR
  - 150 daily frames containing meteorological variables
    - precipitation, sea level pressure, mean, minimum and maximum temperature
  - static DEM
- context (input): 10 frames, prediction: 20 frames
  - the meteorological variables are available as input for the entire 150 days period

Result

- Three baseline models:
  - a naive model - predicts always the average of the context frames
  - Channel-U-Net - based on UNet, by stacking all context frames and predicting all future frames at once
  - Arcon - based on a video prediction model, SAVP (Stochastic Adversarial Video Prediction)

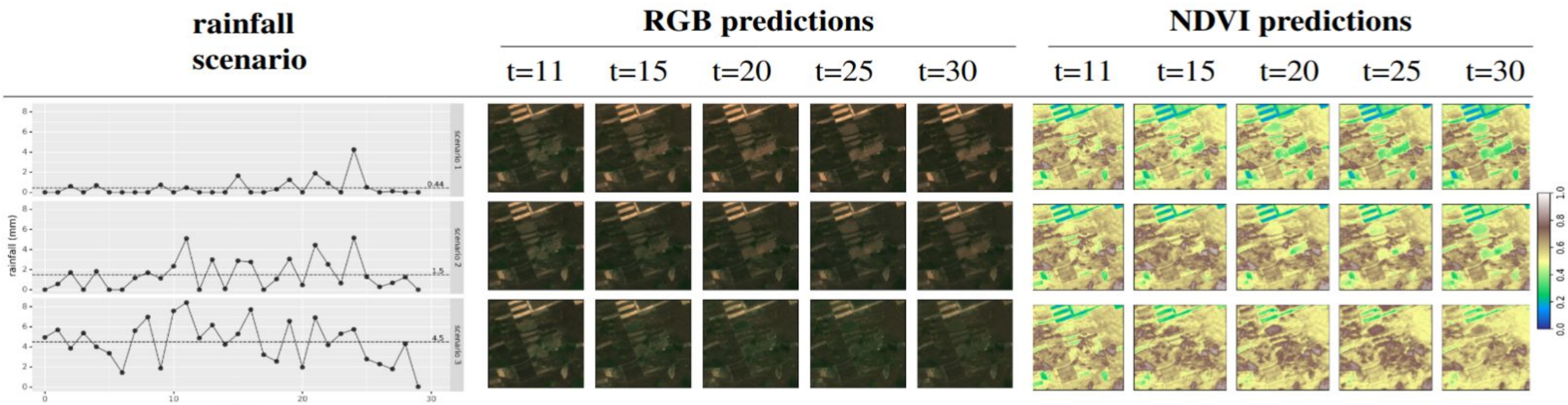
	IID					OOD				
	ENS	**MAD**	**OLS**	**EMD**	**SSIM**	**ENS**	**MAD**	**OLS**	**EMD**	**SSIM**
Persistance (baseline-1)	0.2625	0.2315	0.3239	0.2099	0.3265	0.2587	0.2248	0.3236	0.2123	0.3112
Channel-U-Net (baseline-2)	0.2902	0.2482	0.3381	0.2336	0.3973	0.2854	0.2402	0.3390	0.2371	0.3721
Arcon (baseline-3)	0.2803	0.2414	0.3216	0.2258	0.3863	0.2655	0.2314	0.3088	0.2177	0.3432
ConvLSTM	**0.3266**	**0.2638**	**0.3513**	**0.2623**	**0.5565**	**0.3204**	**0.2541**	**0.3522**	**0.2660**	**0.5125**

Effect of Different Inputs

Test set	Input data	ENS	MAD	OLS	EMD	SSIM
IID	RGBNIR	0.3151 ± 0.0004	0.2576 ± 0.0002	0.3424 ± 0.0004	0.2530 ± 0.0005	0.5162 ± 0.0015
	RGBNIR + DEM	0.3156 ± 0.0003	0.2579 ± 0.0001	0.3424 ± 0.0005	0.2533 ± 0.0006	0.5183 ± 0.0009
	RGBNIR + WEATHER + DEM	0.3266 ± 0.0004	0.2638 ± 0.0002	0.3513 ± 0.0001	0.2623 ± 0.0004	0.5565 ± 0.0017
OOD	RGBNIR	0.3078 ± 0.0005	0.2484 ± 0.0001	0.3426 ± 0.0008	0.2547 ± 0.0007	0.4709 ± 0.0016
	RGBNIR + DEM	0.3084 ± 0.0004	0.2482 ± 0.0003	0.3433 ± 0.0008	0.2564 ± 0.0009	0.4703 ± 0.0019
	RGBNIR + WEATHER + DEM	0.3204 ± 0.0002	0.2541 ± 0.0002	0.3522 ± 0.0006	0.2660 ± 0.0004	0.5125 ± 0.0010

Simulations

- artificially generated various rainfall scenarios by randomly perturbing the original values, within reasonable bounds
- an additional way to validate if the model learned the weather -> land surface relationship
- this also serves as an example of a practical use-case:
- we can feed multiple scenarios (e.g. based on emission scenarios) and analyze their localized impact
- also, seasonal forecasts usually come from an ensemble model => we can take the worst & best case scenarios, or we can also analyze the spread of the predictions as an uncertainty measure


rainfall scenario
RGB predictions
NDVI predictions
t=11
t=15
t=20
t=25
t=30
rainfall (mm)
scenario 1
scenario 2
scenario 3
0.44
1.5
4.5

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Evaluation on Two Special Sets

- Two other evaluation sets are proposed in EarthNet2021:
  - one focused on a region in Germany with a severe drought
    - the context and prediction lengths are different: 20 and 40, resp.
  - one focused on capturing the entire seasonality: 70 context frames (1 year) and 140 future frames (2 years)
- Performance is relatively poor:

	Extreme					**Seasonal**				
	ENS	**MAD**	**OLS**	**EMD**	**SSIM**	**ENS**	**MAD**	**OLS**	**EMD**	**SSIM**
Persistance (baseline-1)	0.1939	0.2158	0.2806	0.1614	0.1605	**0.2676**	**0.2329**	**0.3848**	**0.2034**	**0.3184**
Channel-U-Net (baseline-2)	**0.2364**	**0.2286**	**0.2973**	**0.2065**	**0.2306**	0.1955	0.2169	0.3811	0.1903	0.1255
Arcon (baseline-3)	0.2215	0.2243	0.2753	0.1975	0.2084	0.1587	0.2014	0.3788	0.1787	0.0834
ConvLSTM	0.2140	0.2137	0.2906	0.1879	0.1904	0.2193	0.2146	0.3778	0.2003	0.1685