Modeling time series using LSTMs and TCNs

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1) Dataset

Variables

Variable	Description
GPP	Quantity of CO2 assimilated by the forest through photosynthesis
SWC	Soil water content
VPD	Vapor pressure deficit
Time	format : YYYY-MM-DD HH:MM:SS

Table 1: Variable Descriptions

GPP decomposition

- Mathematical formula:

$$GPP_t = \overline{GPP}_t^{365d} + \overline{GPP_t - \overline{GPP}_t^{365d}}^{24h} + \widehat{GPP}_t$$

where

$$\overline{GPP}^T = \frac{1}{N}\sum_{k=1}^{N} GPP_{t+kT}$$

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$$\overline{GPP}^T = \frac{1}{N}\sum_{k=1}^{N} GPP_{t+kT}$$

  - $\overline{GPP}_t^{365d}$: Annual mean calculated with $N = 2$.
  - $\overline{GPP_t - \overline{GPP}_t^{365d}}^{24h}$: Day-and-night cycle calculated with $N = 7$.
  - $\widehat{GPP}_t$: Anomalies.

GPP Decomposition

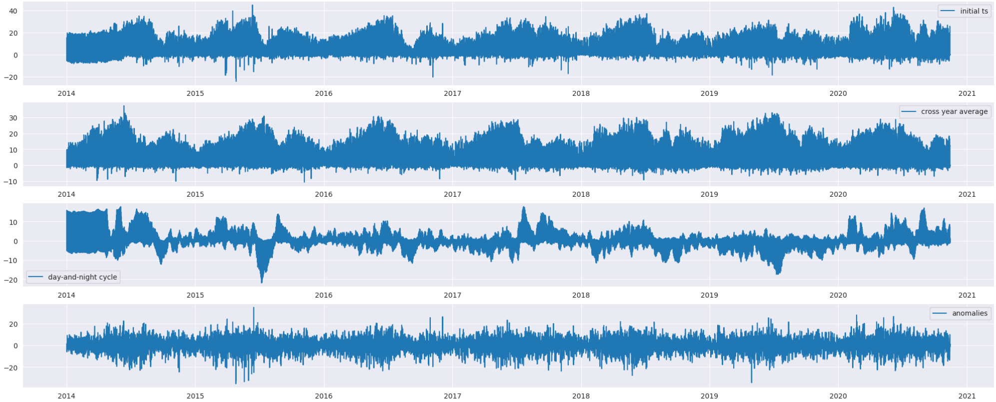

Fig. 1: GPP Decomposition

Time fetaures

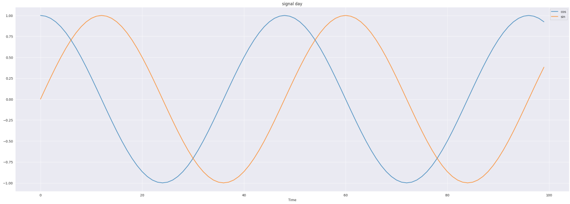

Fig. 2: Day time signal

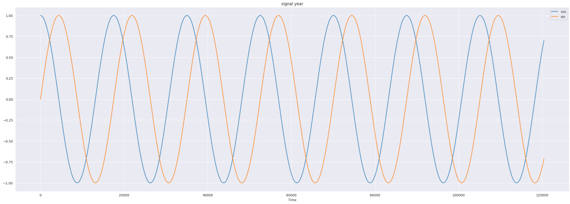

Fig. 3: Year time signal

2) LSTM : Long-Short-Term-Memory

LSTM Inputs & Outputs

- Inputs : Sequences

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$$\left.\begin{array}{l}\text{- Annual GPP}\\ \text{- Day-and-night cycle GPP}\\ \text{- Anomalies}\\ \text{- Time features}\end{array}\right\} \begin{array}{l}\text{from } t-L \text{ to } t\\ L:\text{Sequence length}\end{array}$$

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- Output :

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$$\left.\begin{array}{l}\text{- Annual GPP}\\ \text{- Day-and-night cycle GPP}\\ \text{- Anomalies}\\ \text{- Time features}\end{array}\right\}\quad \begin{array}{l}\text{from } t-L \text{ to } t\\ L:\text{Sequence length}\end{array}$$

- Output :

$$\left.\begin{array}{l}\text{- Annual GPP}\\ \text{- Day-and-night cycle GPP}\\ \text{- Anomalies}\end{array}\right\}\quad \text{at } t+1$$

Model


```
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm (LSTM)                 (None, 128)               69632

 dense (Dense)               (None, 3)                 387

=================================================================
Total params: 70,019
Trainable params: 70,019
Non-trainable params: 0
_________________________________________________________________
```

Fig. 4: Model architecture

Hyperparameters

- Sequence length = 365 (7days)
- Features = 7
- Hidden units = 128
- Optimizer = Adam
- Learning rate = 0.001
- Batch size = 32

Cross year average

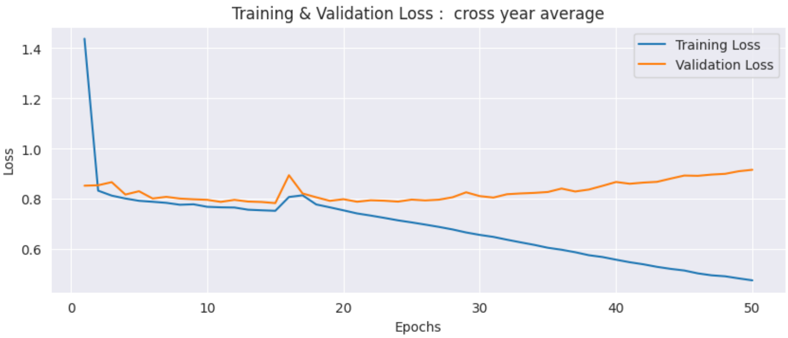


Fig. 5: Training loss VS Validation loss : Cross year average

Day-and-night cycle

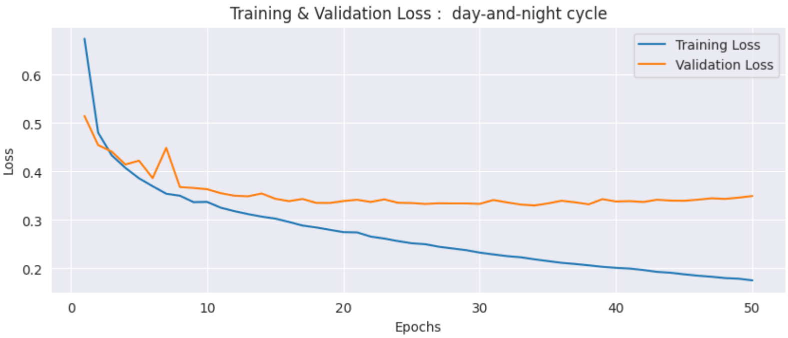


Fig. 6: Training loss VS Validation loss : Day-and-night cycle

Anomalies

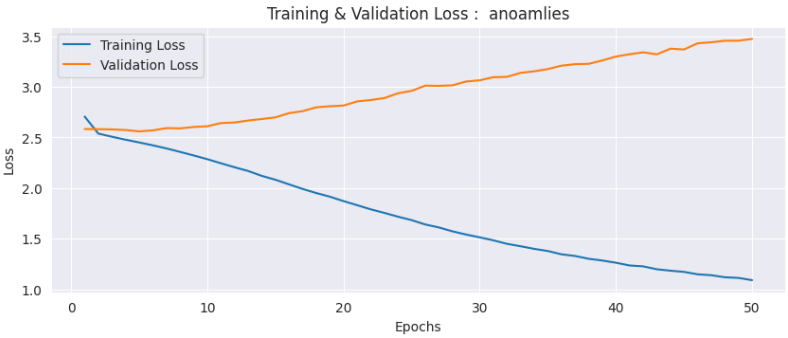


Fig. 7: Training loss VS Validation loss : Anomalies

Hyperparameters

- Sequence length = 700 (2weeks)
- Features = 7
- Hidden units = 128
- Optimizer = Adam
- Learning rate = 0.001
- Batch size = 32

Cross year average

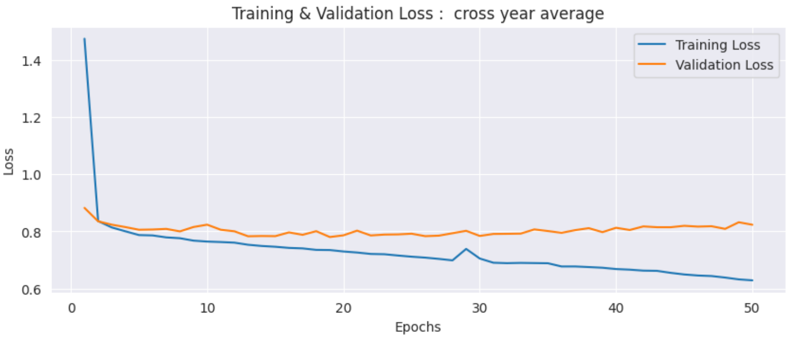


Fig. 8: Training loss VS Validation loss : Cross year average

Day-and-night cycle

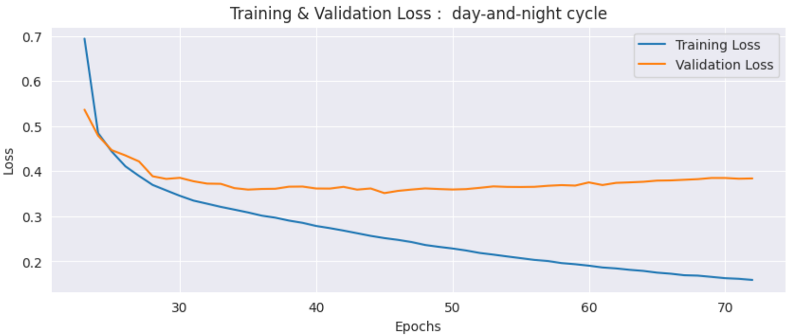


Fig. 9: Training loss VS Validation loss : Day-and-night cycle

Anomalies

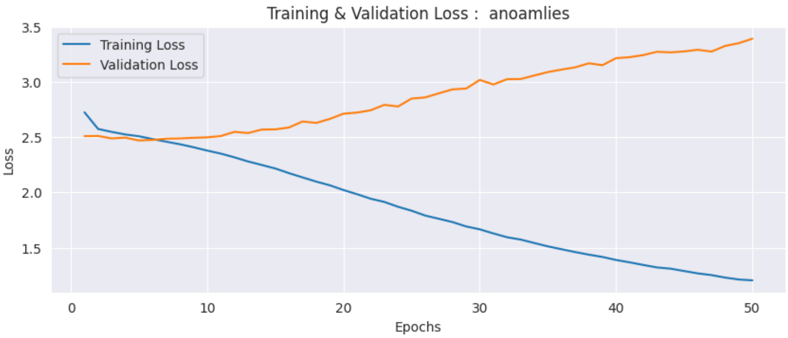


Fig. 10: Training loss VS Validation loss : Anomalies

Model

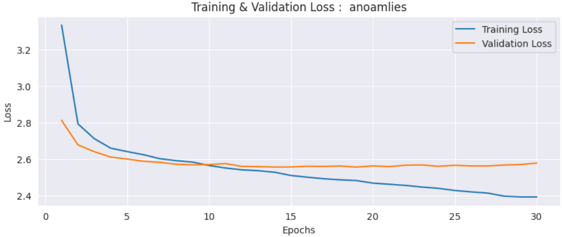

```
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_2 (LSTM)               (None, 365, 64)           18432

 dropout_2 (Dropout)         (None, 365, 64)           0

 lstm_3 (LSTM)               (None, 64)                33024

 dropout_3 (Dropout)         (None, 64)                0

 dense_1 (Dense)             (None, 3)                 195

=================================================================
Total params: 51,651
Trainable params: 51,651
Non-trainable params: 0
_________________________________________________________________
```

Fig. 11: Model architecture

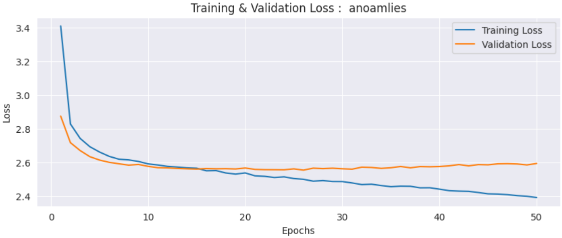
Anomalies

Learning rate $= 0.0001$

Optimizer : Adam



Optimizer : AdamW



3) TCN : Temporal Convolutional Networks

Introducing TCNs

Why privilege TCNs over RNNs ?

- Efficient parallelism.

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- Efficient parallelism.
- Stable gradients (preventing vanishing/exploding gradients..)
- Vision across the sequence => Flexible length inputs.

Architecture

The architecture of TCN consists of :

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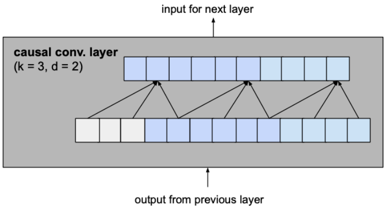
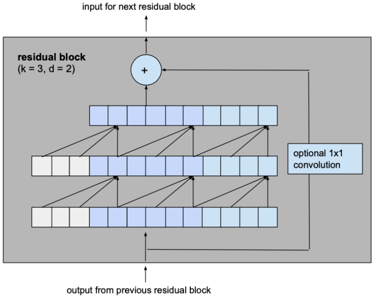
    - Each residual block consists of two causal convolutional layers with the same dilation factor.
    - Introduce complexity to each layer (Activation, Normalization, Regularization)
    - The output of the convolutional layers is added to the input of the residual block through a residual connection.
- Sequential arrangement of residual blocks with increasingly dilations (with blocks).

Residual blocks



(a) Causal convolutional layer



(b) Residual block

Fig. 13: Residual blocks

Architecture

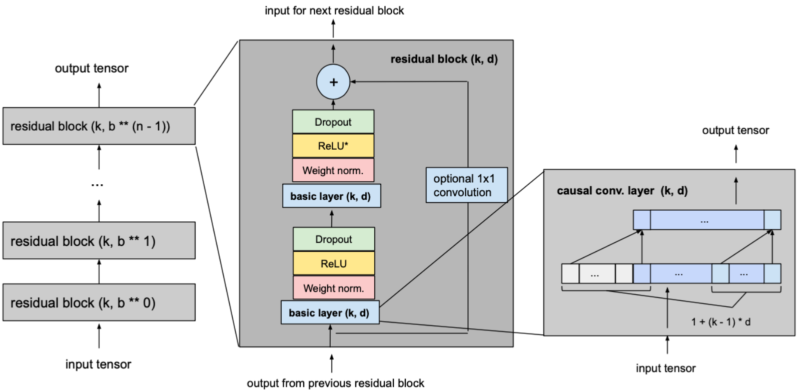


Fig. 14: The entire model

Data preprocessing

- Remove the first year (2014) and last year (2022) (due to too many SWC missing values).

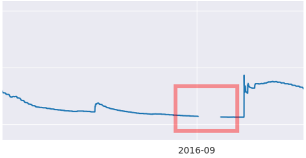


Fig. 15: Missing SWC values on September 2016

Data preprocessing

- Remove the first year (2014) and last year (2022) (due to too many SWC missing values).
- Filling SWC gaps using interpolation and sometimes backward filling.

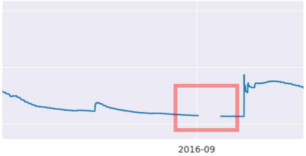
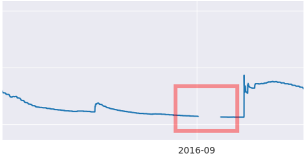


Fig. 15: Missing SWC values on September 2016

- Remove the first year (2014) and last year (2022) (due to too many SWC missing values).
- Filling SWC gaps using interpolation and sometimes backward filling.
- Penalize the loss function based on the number of SWC values that have been filled.



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- Inputs : Sequences

$$\left.\begin{array}{l}\text{- GPP}\\ \text{- VPD}\\ \text{- SWC}\\ \text{- Time features}\end{array}\right\}\quad \begin{array}{l}\text{from } t-L \text{ to } t\\ L: \text{Sequence length}\end{array}$$

- Output : GPP at t+1

Hyperparameters

- Sequence length = 400 (>one year)
- Features = 7
- Channels = [32, 64, 128]
- Kernel size = 3
- Learning rate = 0.001
- Dropout = 0.2
- Batch size = 32
- Loss function : MSE (with penalization)

TCN Training

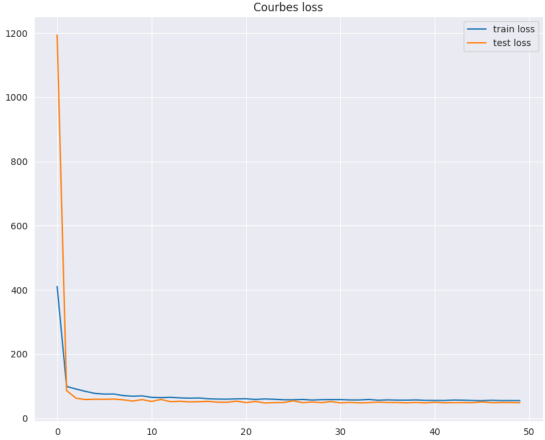

Fig. 16: Training loss VS Validation loss using TCN

Conclusion

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Overall good performance of TCN.

Perks :

- Fast &optimal convergence.
- Not time-consuming.
- No need for manual GPP decomposition.
- Interpretability.

Drawbacks :

- Requires long sequences to capture temporal patterns $=>$ significant computational resources.