Characterization of Alpine Pastures using Multitemporal Earth Observation Data within the Climate Change Framework

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Climate Change | **Alpine Pastures** | **Rising temperature** | **Effects on biomass** | **Mitigation and adaptation strategies**

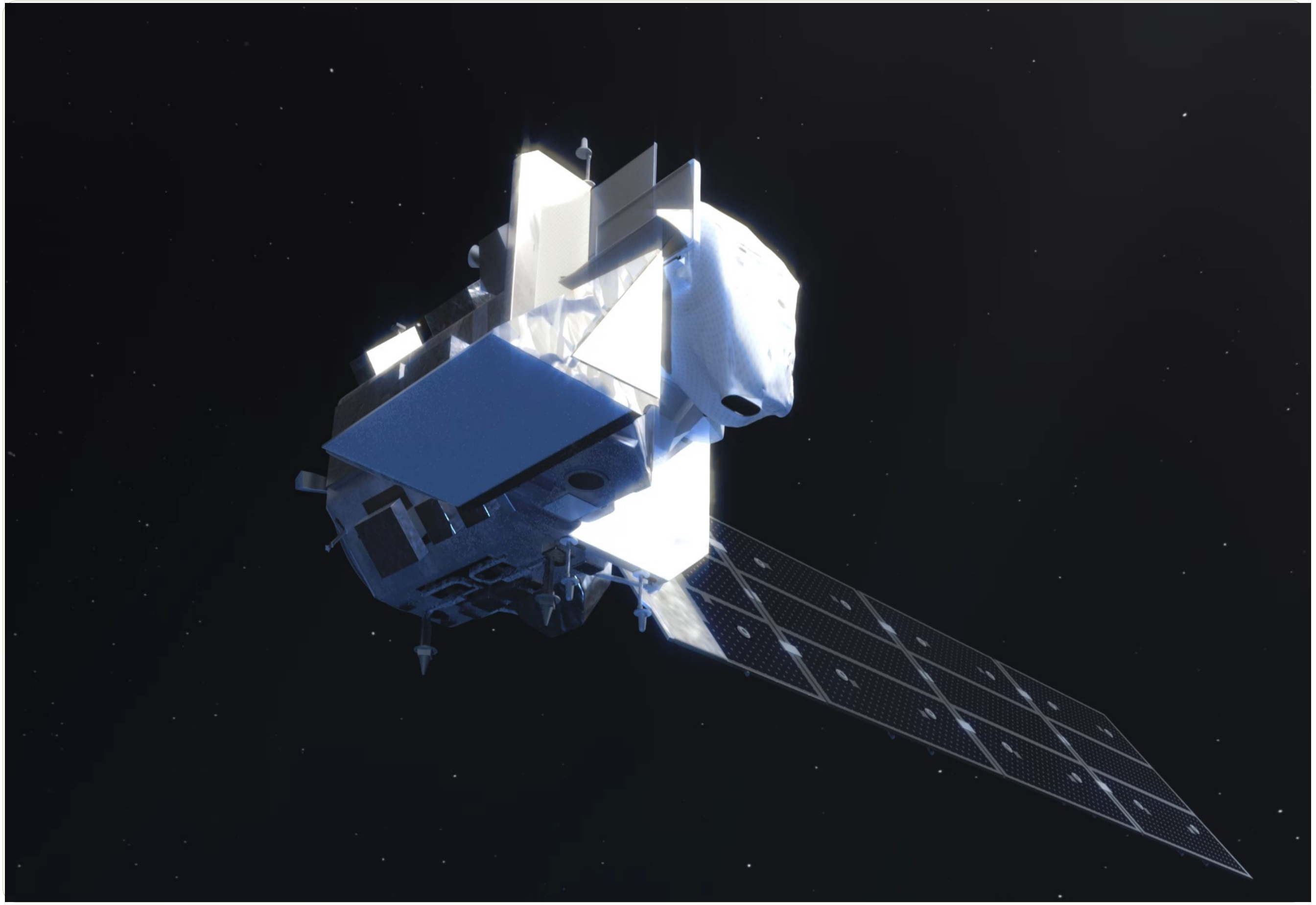
Aims

- Developing a remote-sensed based continuous monitoring tool of alpine pastures reaction to climate change
- Modeling and mapping alpine pasture reaction to rising temperature
- Preliminary quantifying the role of each environmental pattern such as altitude, aspect etc… for further deeper studies considering the entire alpine chain
- Provide useful information to public technicians, agronomists, foresters and shepherds as well as policy makers.

Landsat thermal monitoring

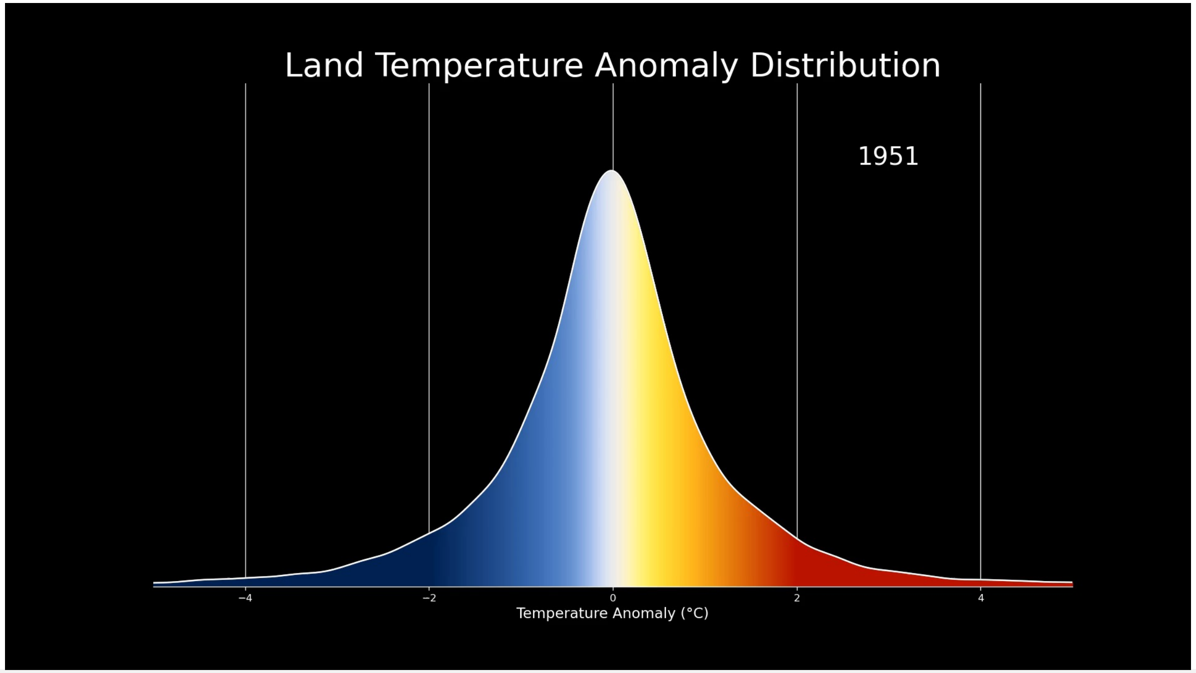
Satellite Remote Sensing Termography role in vegetation assessment

- LST monitoring from 1984 till today each 16 days worldwide
- The unique satellite missions with long-term ongoing thermal sensors with medium-high GSD 30-100 m



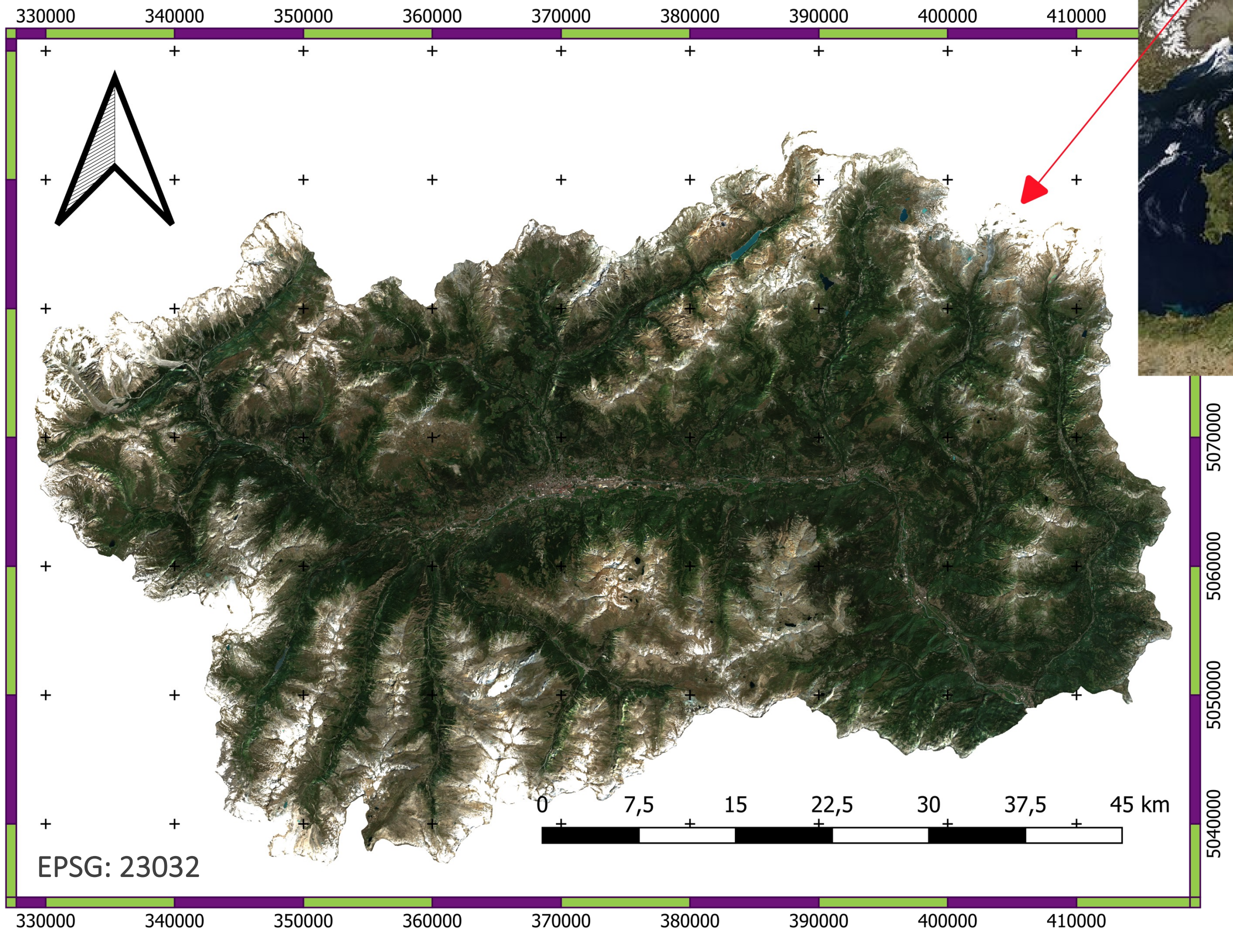
Main Aim

Modeling and measuring thermal trends in Aosta Valley alpine pasture areas by **exploring possible drivers** influencing these trends with particular regard to **topographic-environmental** patterns and biomass



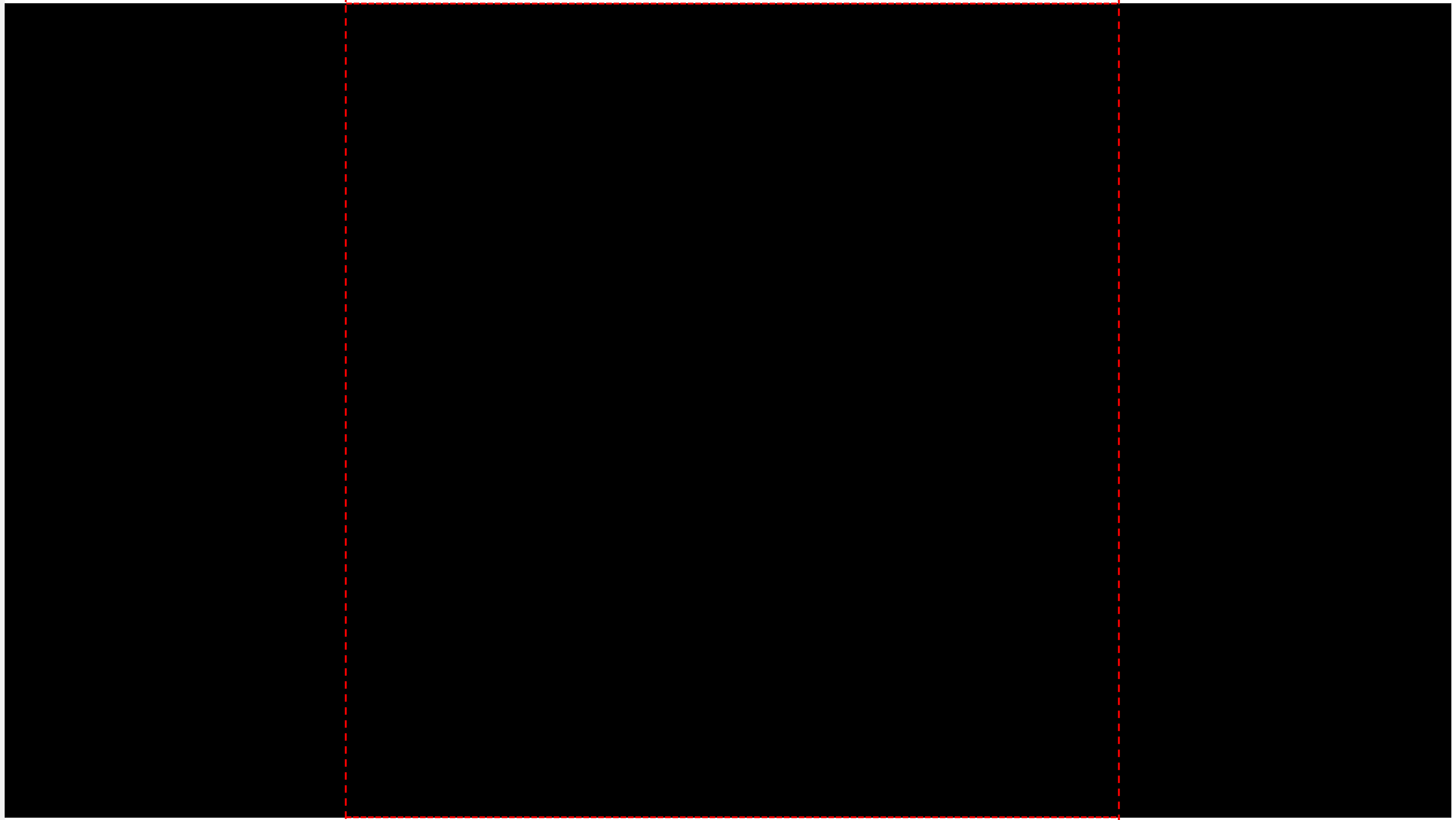
Ph T.O.

AOI – Area of Study



Material and Methods

TIME RANGE ANALYZED (tra)



39 years
considering Landsat 4-9 missions

1984 2022

More then 900 images considered over the AOI

Landsat 7 images after May 31, 2003 were filtered out due to SLC failure

Workflow

LST Calibration

- ✓ TOA Brightness temperature considered (T1_TOA & Level 2 Collections used in GEE)
- ✓ Clouds / shadows masking
- ✓ SMW Algorithm and Jiménez-Sobrino approach followed in (tra):

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{RED}}{\mathrm{NIR} + \mathrm{RED}} \quad (1)$$

Google Earth Engine

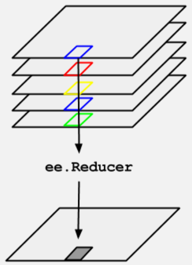
$$\mathrm{FVC} = \frac{\mathrm{NDVI} - \mathrm{NDVI_S}}{\mathrm{NDVI_V} - \mathrm{NDVI_S}} \quad (2)$$

$$\varepsilon = FVC\varepsilon v + (1 - FVC)\varepsilon s \quad (3)$$

$$\mathrm{LST} = \mathrm{A_i}\left(\frac{\mathrm{T_b}}{\epsilon}\right) + \frac{\mathrm{B_i}}{\epsilon} + \mathrm{C_i} \quad (4)$$

LST & NDVI time-series (ts) maps

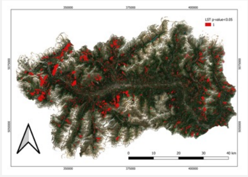
- ✓ All images filtered Savitzky-Golay and regularized to before creating composites
- ✓ Yearly 3-months mean composite creation within the calendar range June-August

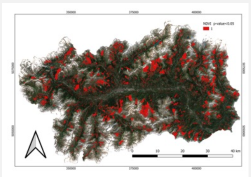


- ✓ Stacks of 39 images/years (mean composites) mapped
- ✓ Clipping on Pasture parcels extracted from cadastre within Landsat pixel GSD

Modeling & Mapping

- ✓ Gain and offset values extracted by trends modelled and mapped
- ✓ Pettitt's test performed to exclude break-points in ts
- ✓ In unchanged pixels a 1st order polynomial fitting
- ✓ Significance of gain tested p-value < 0.05 and mapped





- ✓ Binning onto terrain components, NDVI and LST gain and offset and relationship testing

Trends extraction

LST

$$LST(kelvin) = \alpha * t + \beta$$

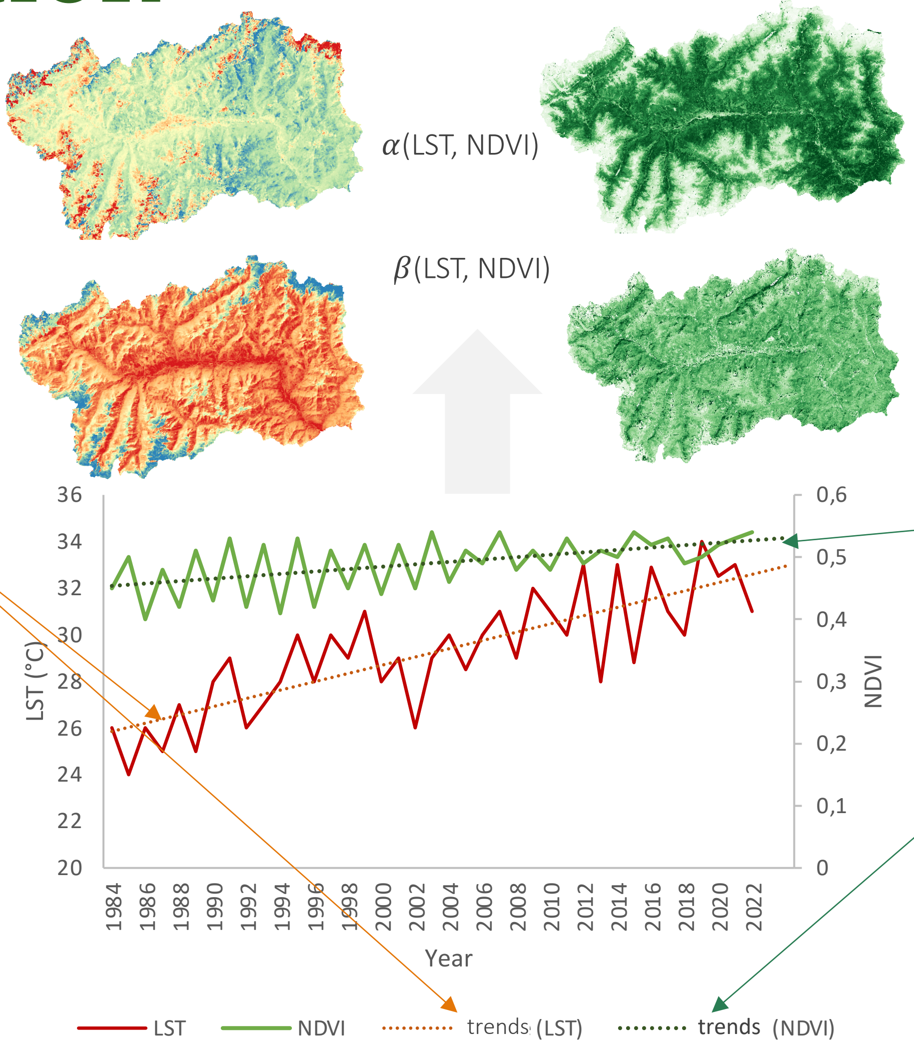
Where:

α: GAIN

β: OFFEST

t: time expressed in lenght of the ts (in the eg. 1-39)

LST estimation of measurement uncertainty



NDVI

$$NDVI = \alpha * t + \beta$$

Where:

α: GAIN

β: OFFEST

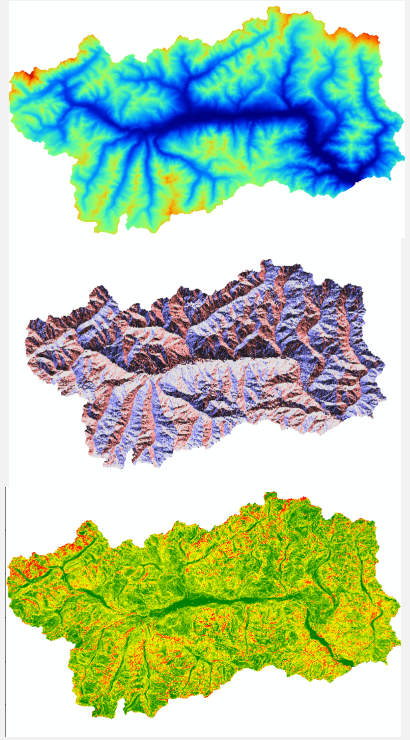
t: time expressed in lenght of the ts (in the eg. 1-39)

NDVI estimation of measurement uncertainty

Terrain and binning

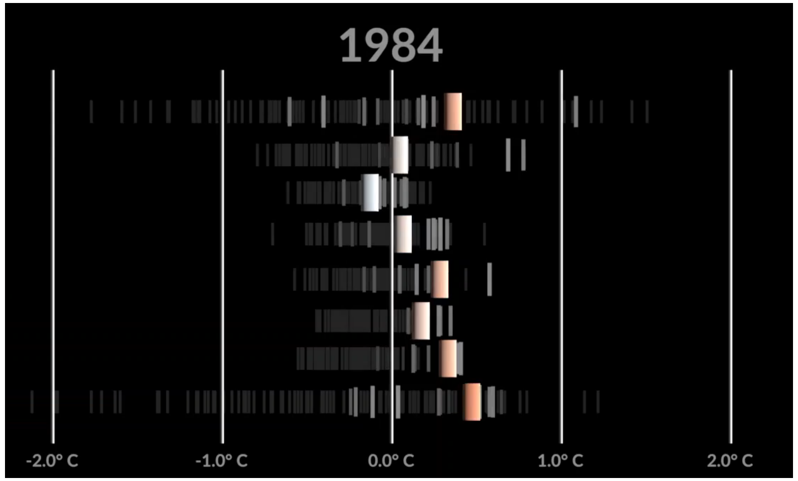
Terrain features

Starting from Digital Terrain Model downloaded from SCT Aosta Valley Geoportal aspect and slope were computed



Results answering….

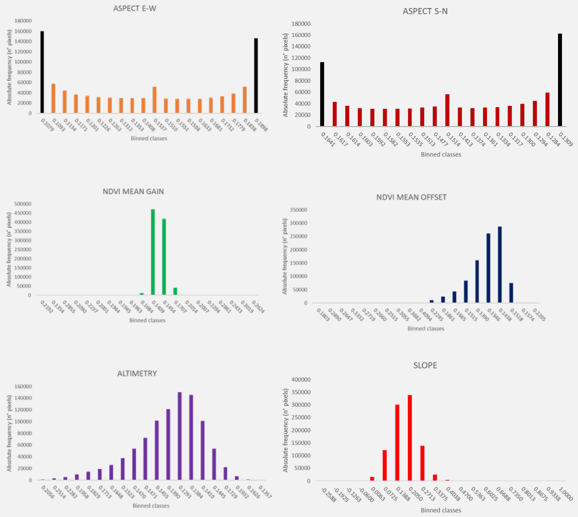
- Which is the Aosta valley pasture response to climate change?
- In which way environmental factors influencing LST gain?



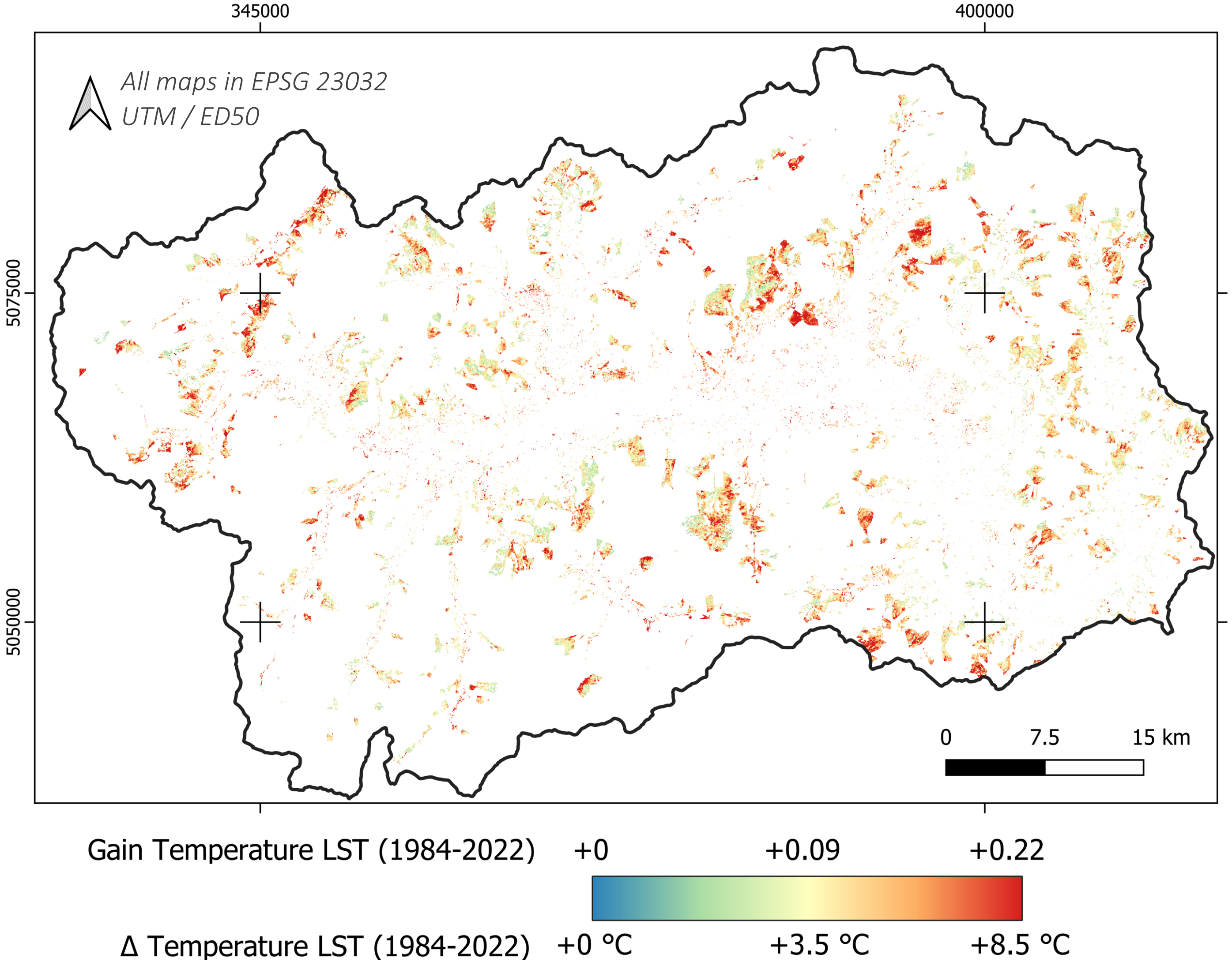
Binning

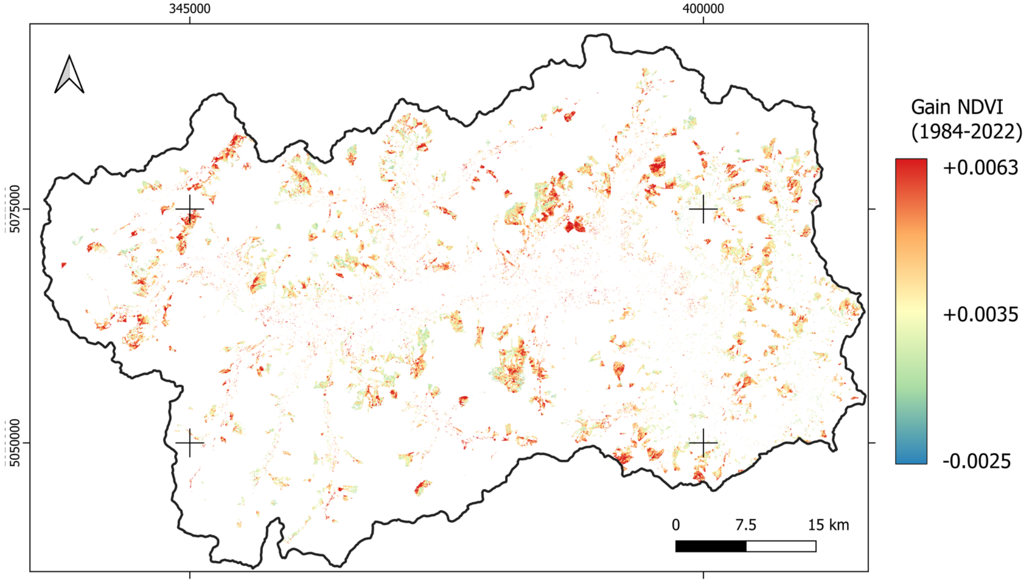
20 bins involving:

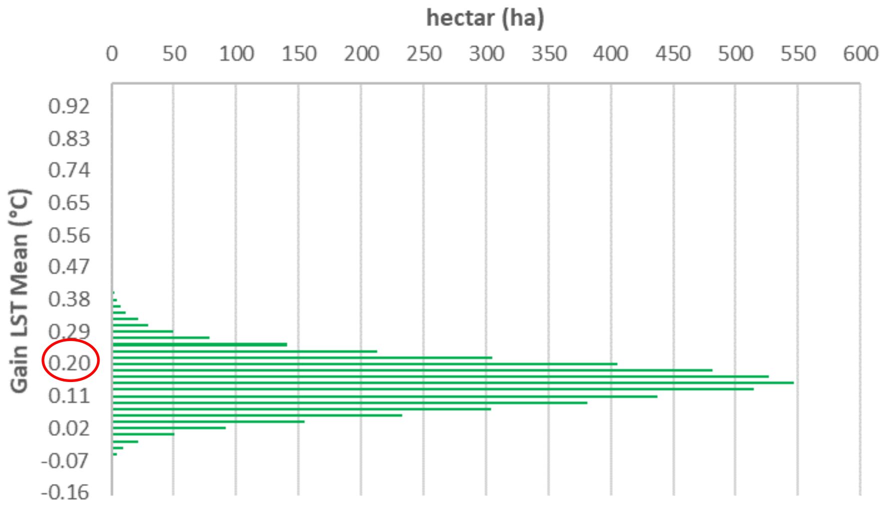
- Aspect (step each 0.1 rad)
- Slope (step each 0.1 rad)
- Altitude (step each 150 m)
- NDVI mean gain (step each 0.003)
- NDVI mean offset (step each 0.1)



Results

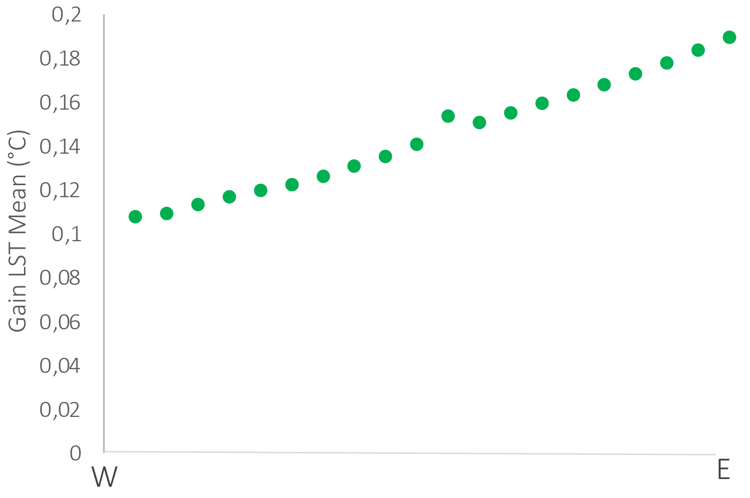






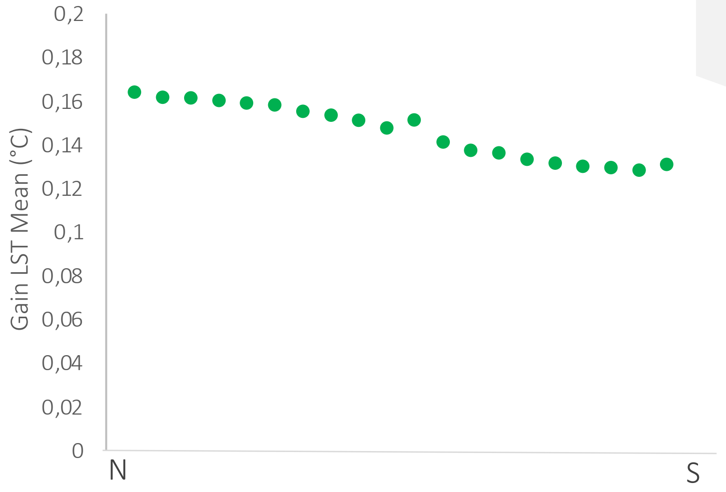
- About 550 hectares of pastures from 1984 to 2022 have suffered a LST increase of almost 6°C
- Almost 2900 ha of pastures have suffered an LST increase in the last 39 years upper to 6°C. At the same time an increase in NDVI occurs

Terrain features effects on LST trends



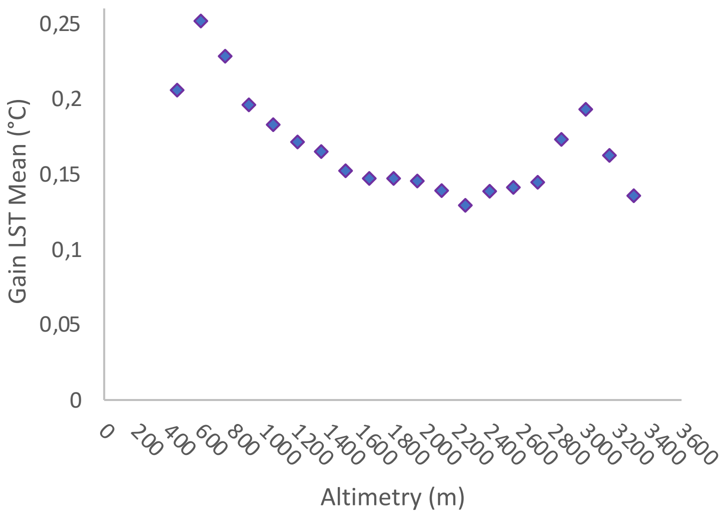
LST Mean Gain is higher in Aosta Valley Eastern pastures then in the Western

Eastern pastures have a steeper increase in LST then Western



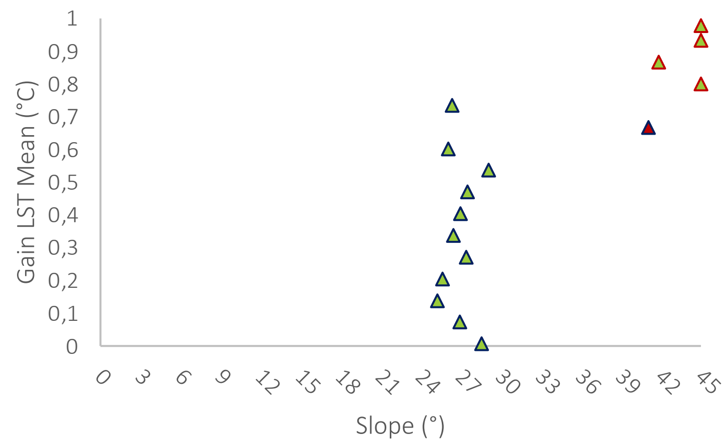
LST Mean Gain is higher in Aosta Valley Northern pastures then in the Southern

Northern pastures are suffering a steeper increase in LST then Southern, nevertheless the gain amplitude is not so wide then in E-W

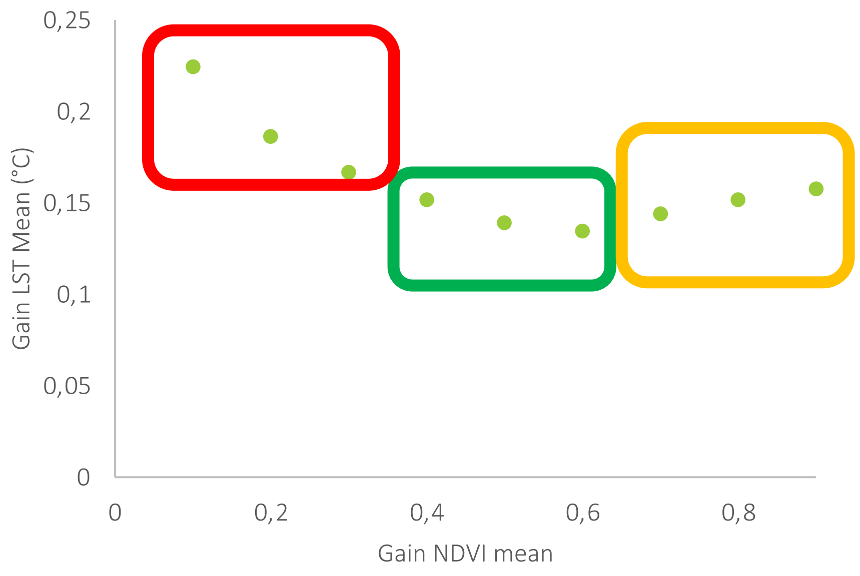


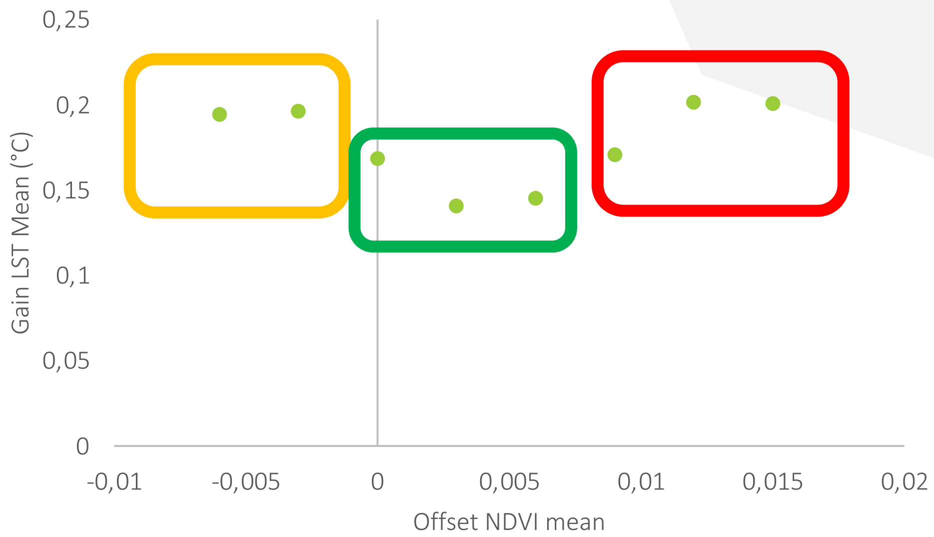
LST Gain mean is higher in Aosta Valley in the bottom of the valley however between 2000-3000 m re-start to rise up

Bottom pastures are more exposed to rising temperatures like those located at high altitude. In this last case this is probably due to the major presence of tare (like rocks and presence and lower biomass)



No relationship with the slope





In pastures where the biomass has always expressed a high value of vigor and presence, it seemed to be able to mitigate the thermal increase forcing (observe the yellow and green cluster gain and offset respectively)

In poorly vegetated pastures or in pixels subjected to a change of cover due to recolonization by herbaceous species and therefore with sparse and reduced vegetation (low gain of NDVI) there are more marked thermal gain (observe also offset) see red clusters

Conclusion

To sum up in key points

- In the last 39 years pastures LST increased up to ≃9°C
- N-E pastures are affected by a steeper increase in temperature then those in S-W respecting to the past
- Pastures at the bottom of the valley and near peaks are more affected by the LST rising up
- A slightly mitigation seems to be offered only by pastures with continuosly higher tenure of biomass
- Almost 2900 ha of pastures have suffered an LST increase upper to 6°C in the last 39 years

Thank you – Merci – Danke – Grazie

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Deadline for manuscript submissions:
31 May 2023

Message from the Guest Editors

The following topics are strongly encouraged:

- Research experiences relating to the potentialities and limits of AI in supporting remote-sensing-based applications in agricultural and forest contexts.
- AI for data integration aimed at maximizing the exploitation of spatial, temporal, and spectral features of sensors from different platforms with special concern about scalable approaches relying of the adoption of RPAS, aerial and satellite datasets.
- AI for supporting remote-sensing-based services in agriculture and its relationship with data integration and analysis systems (DIASs), high-performance computing (HPC) and Internet of Things (IoT).
- AI for hyper/multi-spectral image interpretation/classification.
- AI for point cloud interpretation from digital photogrammetry and LiDAR systems.
- AI for time trends analysis and interpretation (e.g., crop phenology detection and forecasting, drought trend modelling, etc.).
- AI to support decision-support systems for crop management (irrigation, fertilization, crop protections, etc.) based on the integration of satellite, meteorological and field data.

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