Infrared Emissivity Estimation from VIS-NIR Reflectances by Neural Network Learning : Benefit to LST Estimation.

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Manpower Founds:

Why work on emissivity estimation?

- **Emissivity is inseparable from the Ts estimation**
- **Need accurate emissivities for accurate Ts**

TRISHNA NeDT = 0.2K
ΔLST<0.2K => ΔLSE<0.01 *

** Qin et al., IJRS (2001)*
value for $\lambda = 10-12\mu m$

- **Emissivity** is **difficult to measure in laboratory and quite impossible in field**
- **Part of the ill-posed problem to estimate LST when multi-bands**

Work context => TRISHNA mission (CNES/ISRO cooperation):

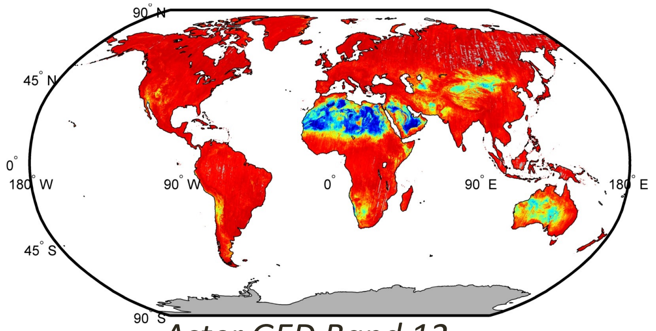
❑**4 thermal bands** [8.65, 9.0, 10.6, 11.6] µ

Global context and RS products

Nowadays, **emissivity for remote sensing approach appears to be a well known parameter...**

- ASTER Global Emissivity Database
- MODIS MOD21 Emissivity Product
- Spectral libraries

NASA/JPL/USGS products



Aster GED Band 12

However, there is still probably room for improvement.

LSE_λ may varies over **time,**
with **humidity of materials,**
with **spectral band, view and solar angle...**

Solve emissivity to Ts estimation problem

If unique thermal band :

- **Classification Maps** and Tables
- **Adapt global maps** from multi-band
- **Function of Vegetation Indices** (VIS-NIR bands)

If multi-thermal band (≥3) :

- Simultaneous **Temperature and Emissivity Separation**

(Gillespie et al, 1999, Vidal et al. 2022)

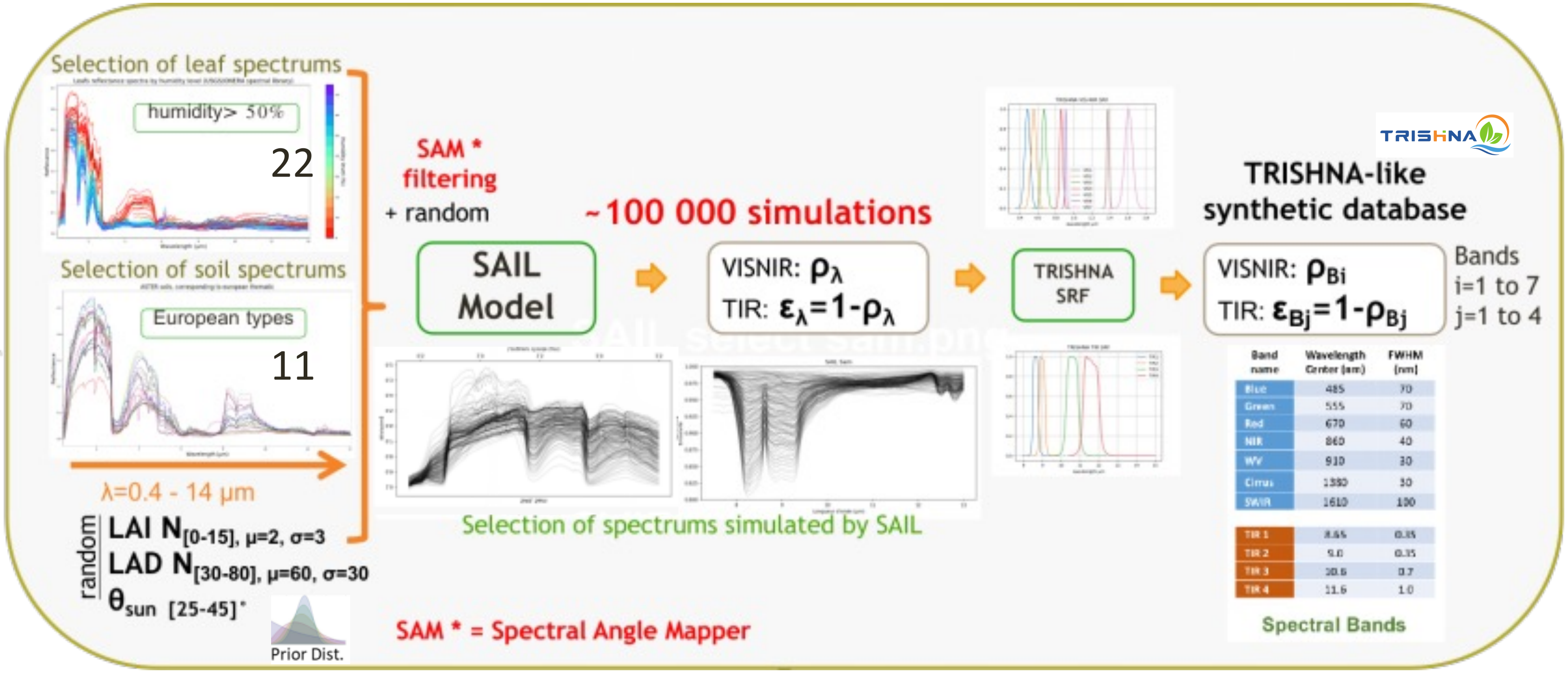
Try hybrid...

A- Development of a synthetic TRISHNA-like database

1st : Build a random synthetic database of continuous spectra [*0.4-14*μm]

=> As representative as possible of **natural covers** (forest, crop, prairie, bare soil...).

=> From leaf spectra to vegetated natural surface spectra (**pixel scale**).



VISNIR and TIR

synthetic database of TRISHNA-like values

ρ_{B1} to ρ_{B7}

ε_{TIR1} to ε_{TIR4}

~100 000 values

2nd : Convert continuous spectra to TRISHNA-like reflectances (ρ) and emissivities ($\varepsilon = 1 - \rho$) based on the TRISHNA-Spectral Response Functions (*SRF*)

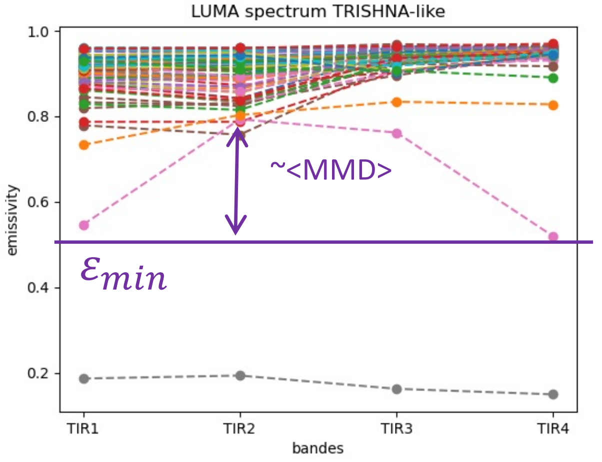
A-1 Learn MMD relation for TES application

Determination of coefficients **[a,b,c] of the** **relationship** between
the minimum emissivity (ε_{min}) and the Maximum-Minimum Difference (**MMD**)

synthetic database of TRISHNA-like LSE values

ε_{TIR1} to ε_{TIR4}

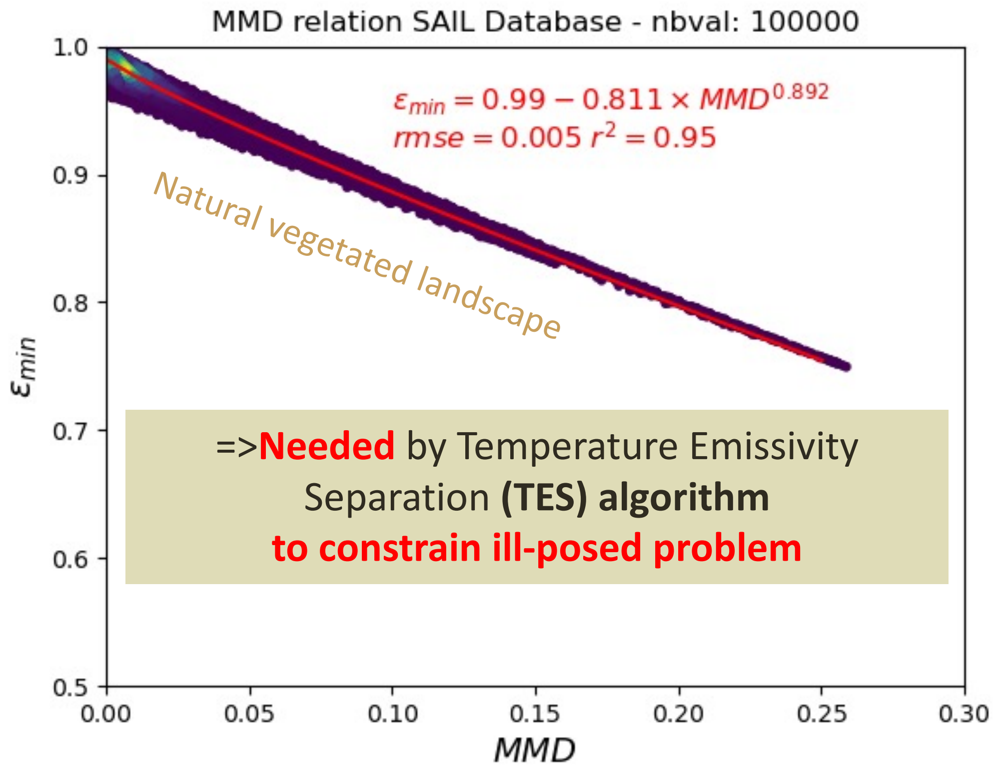
$\boxed{\varepsilon_{min}=a+b\times MMD^{c}}$



$$\varepsilon_{min} = min(\varepsilon[j])$$

$$MMD = max(\beta[j]) - min(\beta[j])$$

with $$\beta[j] = \frac{\varepsilon[j]}{\frac{1}{4}\sum_{j=4}\varepsilon[j]}$$ j =TIR1 to TIR4



=>**Needed** by Temperature Emissivity Separation **(TES) algorithm**
to constrain ill-posed problem

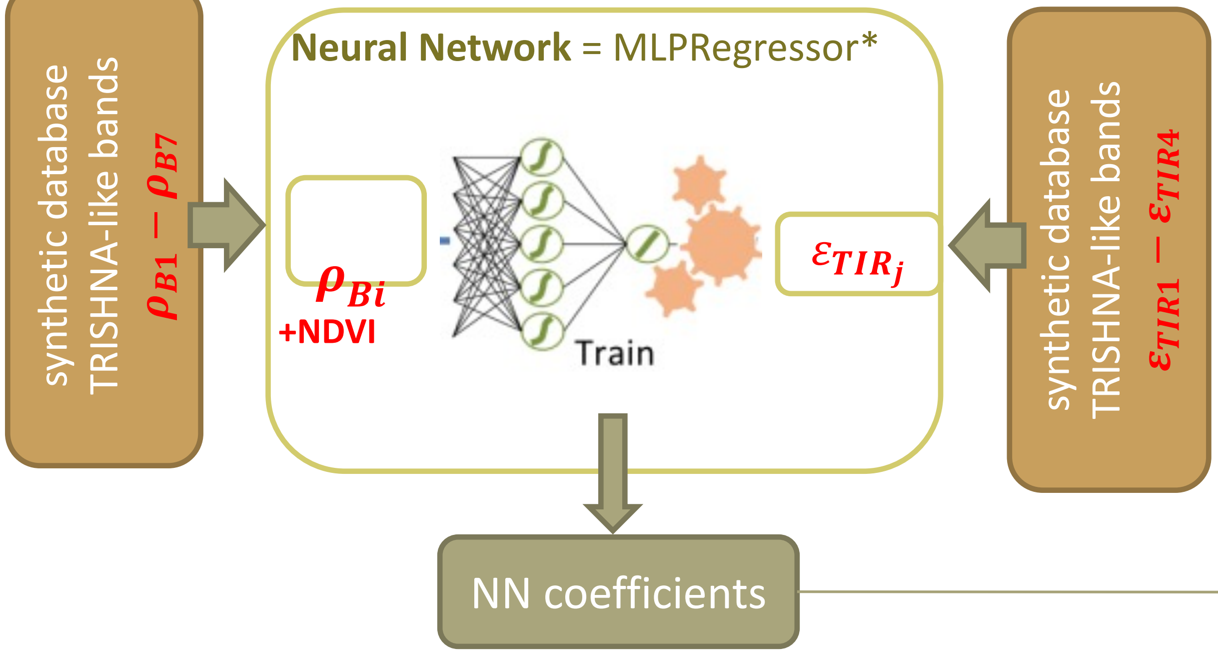
Note: no water, no snow, no manmade material

A-2 Learn empirical relations between $\rho_{VIS\text{-}NIR}$ and ε_{TIR}

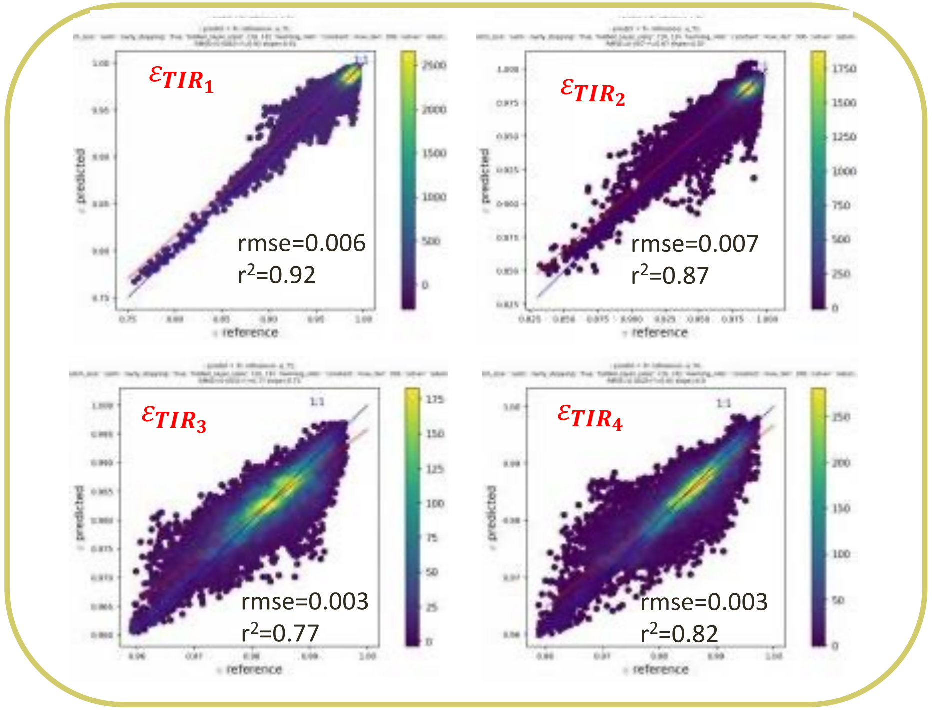
Hypothesis: suppose visible-nir reflectances contain information to determine thermal LSE

- Use of the synthetic TRISHNA-like database for relationship learning
- Use of a Neural Network approach

3/4 for **learning phase**



1/4 for **validation phase**



*Scikit-learn Python library

Application: Airborne Hyperspectral Data, AHSPECT 2015 Campaign

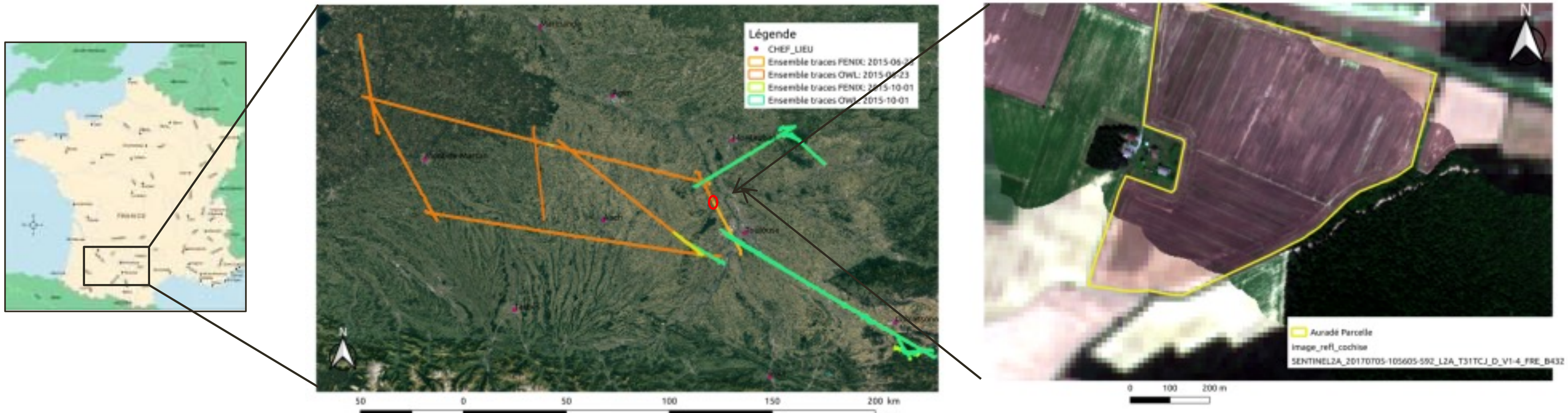
(ESA - EUFAR - CNRM)

- **June 23 2015 / Sunny and warm day**
- **2 hyperspectral sensors:**

  FENIX λ = [0.4:0.005:2.5] μm, 421 bands **2m** spatial resolution

  OWL λ = [7.5:0.01:13] μm, 551 bands

only 1 track used

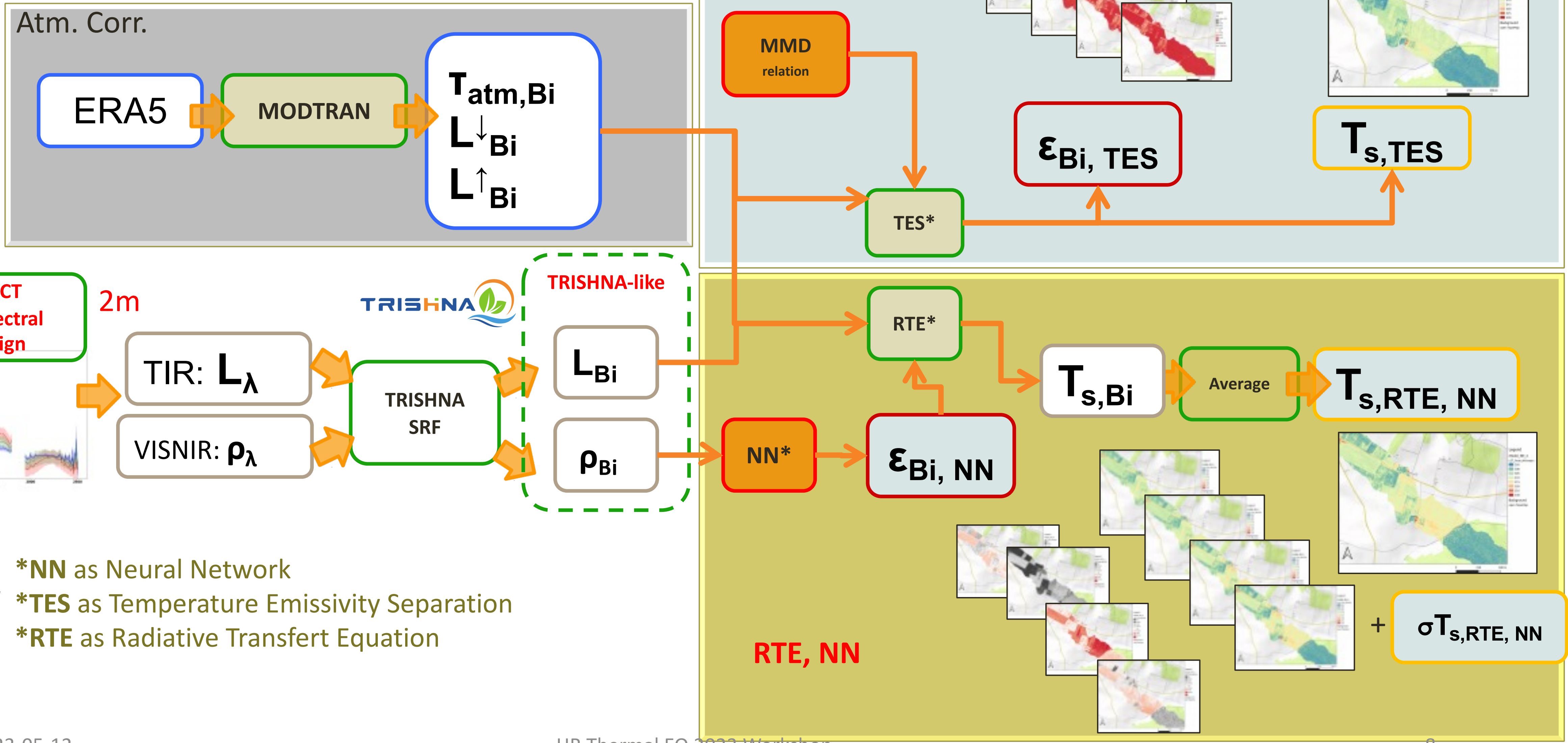


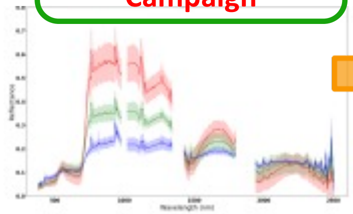
Acquisition path lines

RVB Fenix with Landsat as background

- **Atmospheric compensation for VIS-NIR** performed by ONERA (**COCHISE** & **ERA5** for atmo. profiles)
- **Thermal atmospherical parameters** obtain with **MODTRAN** & **ERA5** atmo. profiles

LSE & LST estimation flow sharts (2 approaches)

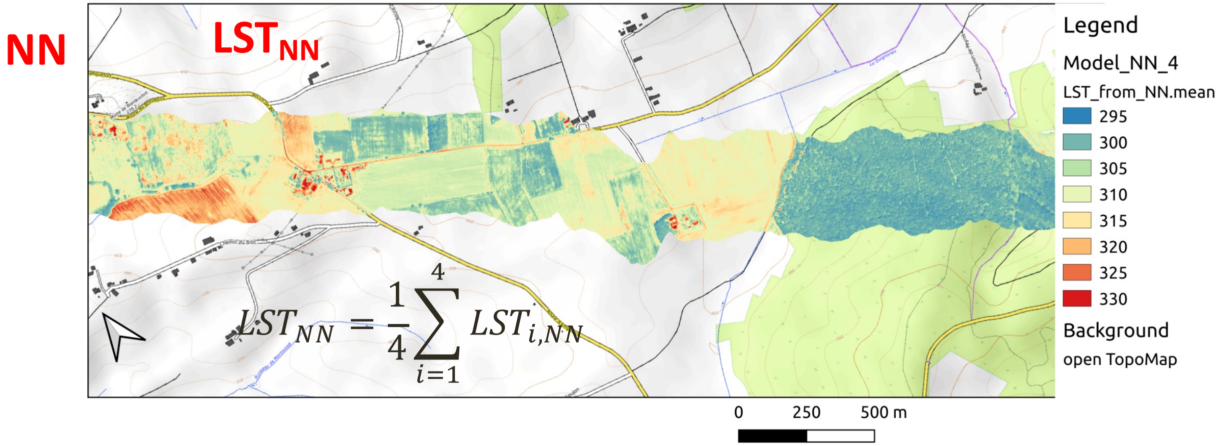




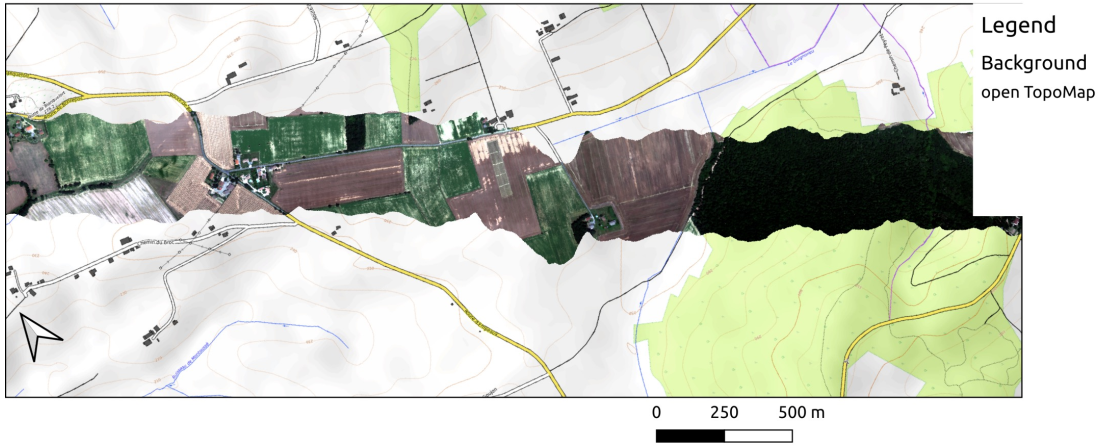
*NN as Neural Network
*TES as Temperature Emissivity Separation
*RTE as Radiative Transfert Equation

AHSPECT airborn June 23 2015

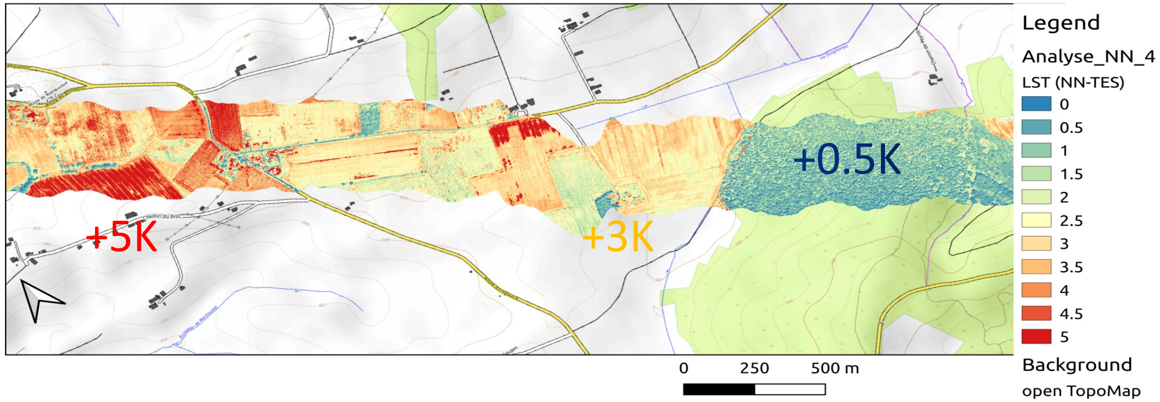
Spatial LST NN vs. TES



$$LST_{NN} = \frac{1}{4}\sum_{i=1}^{4} LST_{i,NN}$$



LST_{NN}-LST_{TES}



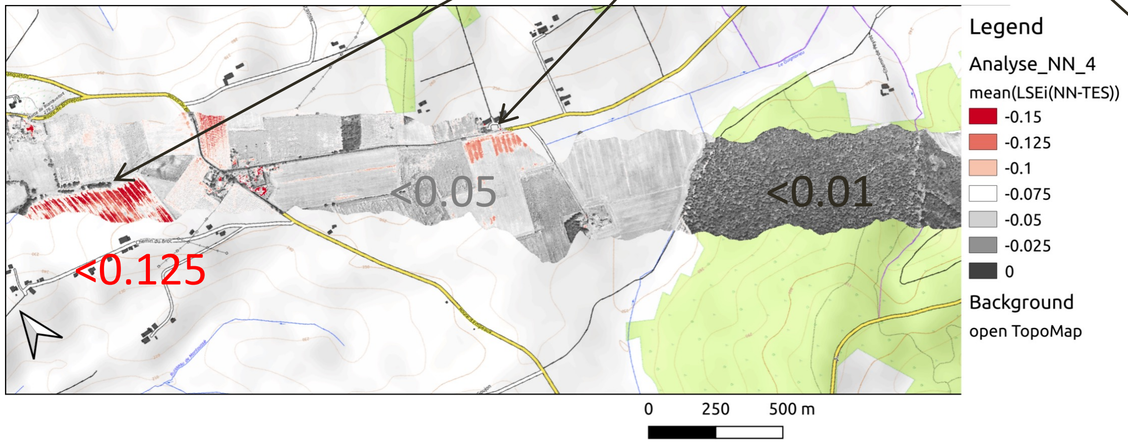
$LST_{NN} > LST_{TES} \Rightarrow \Delta LST > 0$

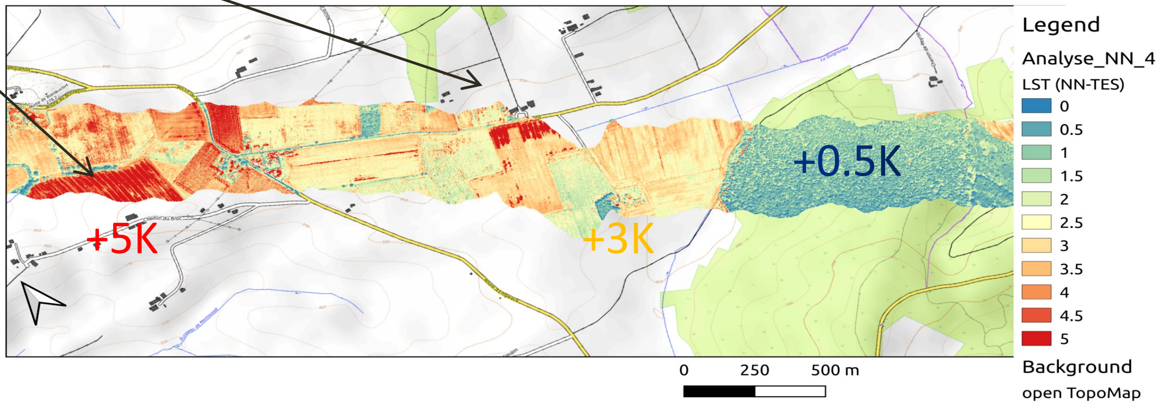
Spatial LSE NN vs. TES

desagreement

$$\overline{\Delta LSE} = \frac{1}{4}\sum_{i=1}^{4} LSE_{i,NN} - LSE_{i,TES}$$

LST_{NN}-LST_{TES}





Hypotesis :

Surface characteristics out of learning database ?

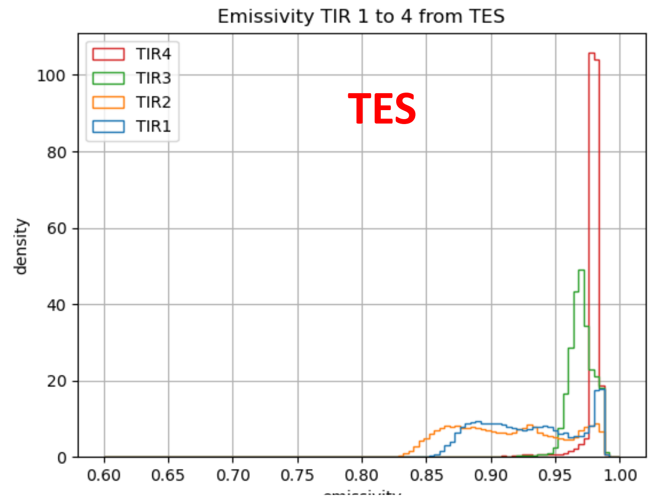
Or far from MMD relation..?

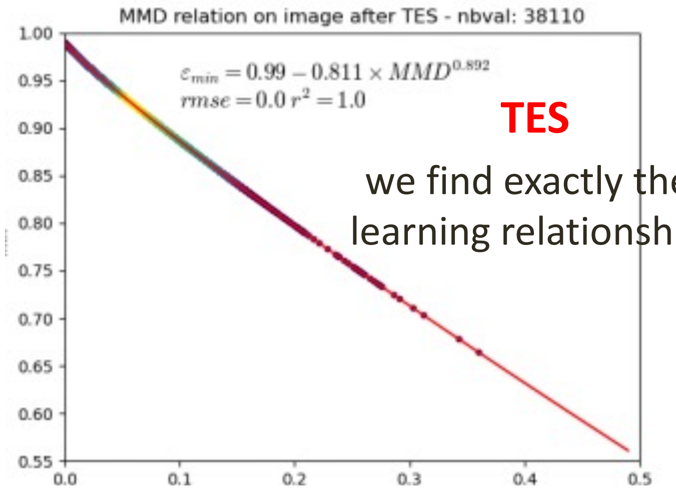
=> Need specific spectrum measurements

$LST_{NN} > LST_{TES} \Rightarrow \Delta LST > 0$

Comparison Between LSE Estimates

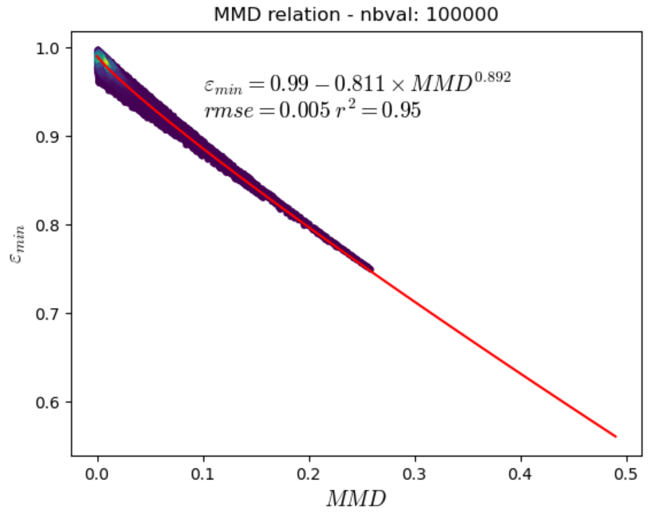
Learning database
«reference»

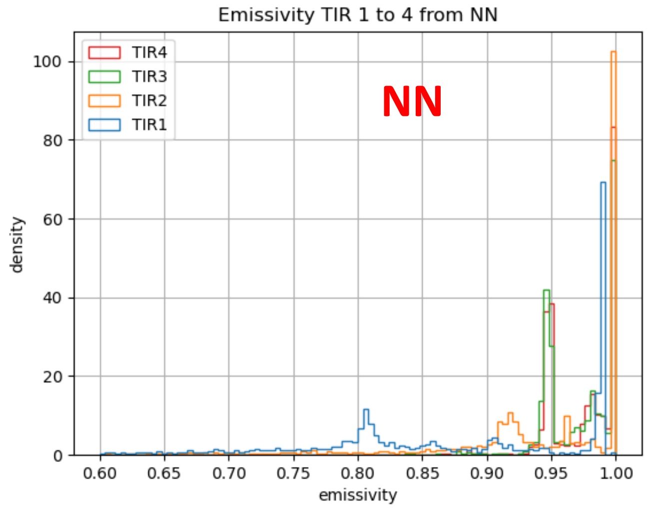


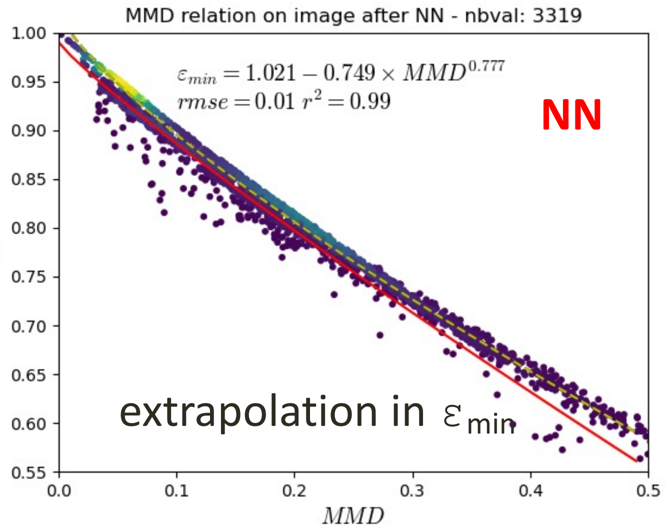


we find exactly the learning relationship

=







extrapolation in ε_{min}

the MMD relationship from LSE_{NN} overestimates the database relationship

in general for all TRISHNA TIR bands:

$LSE(TIR_i)_{NN} < LSE(TIR_i)_{TES}$

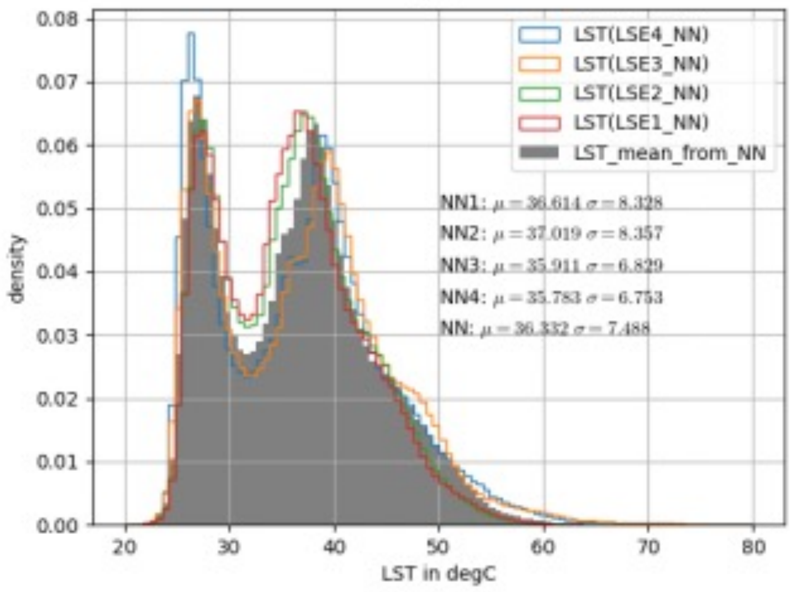
Distribution of LST in image: NN vs. TES

$LSE(TIR_i)_{NN} < LSE(TIR_i)_{TES}$

$LST(TIR_i)_{NN} > LST(TIR_i)_{TES}$

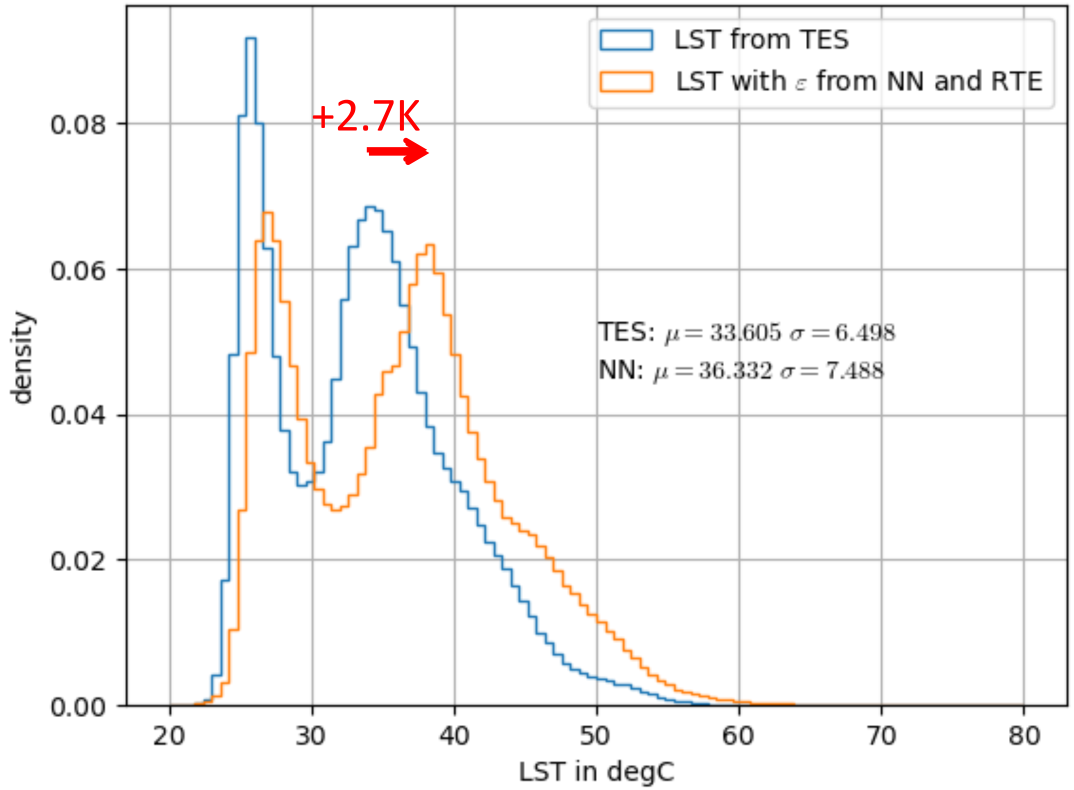
NN

LST(ε$_i$)

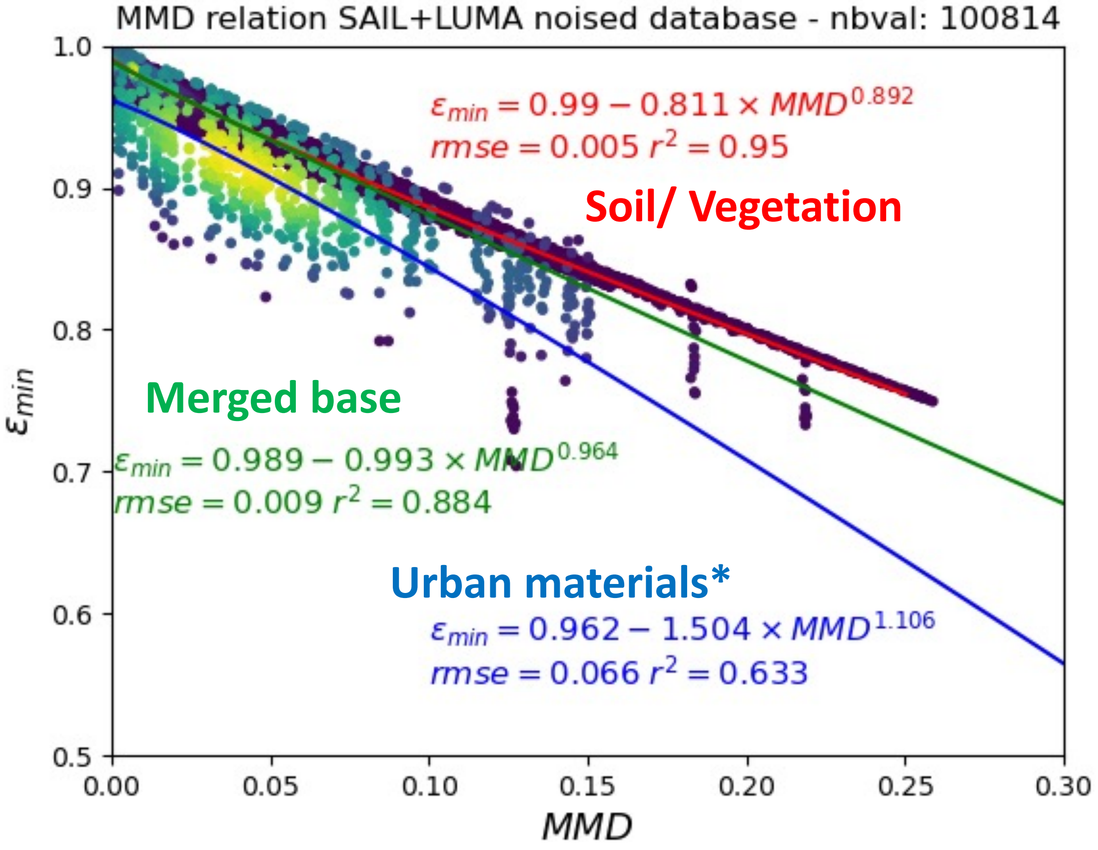


$$LST_{NN} = \frac{1}{4}\sum_{i=1}^{4} LST_{i,NN}$$

NN vs TES



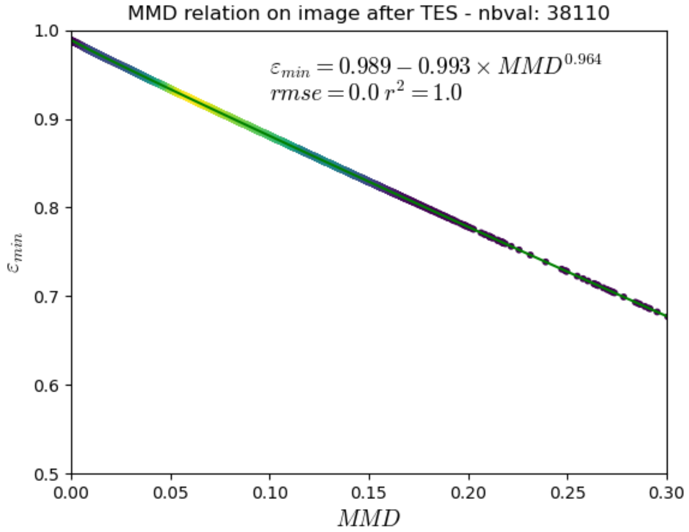
Add spectrum from Material Database (+Noise) to Synthetic Database

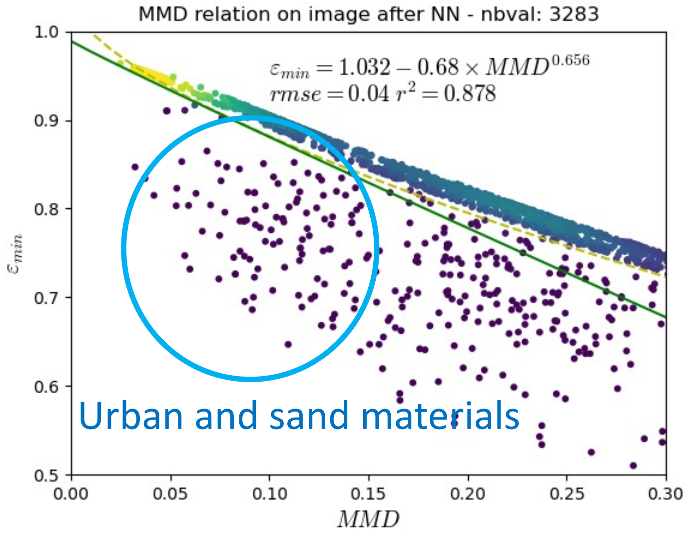


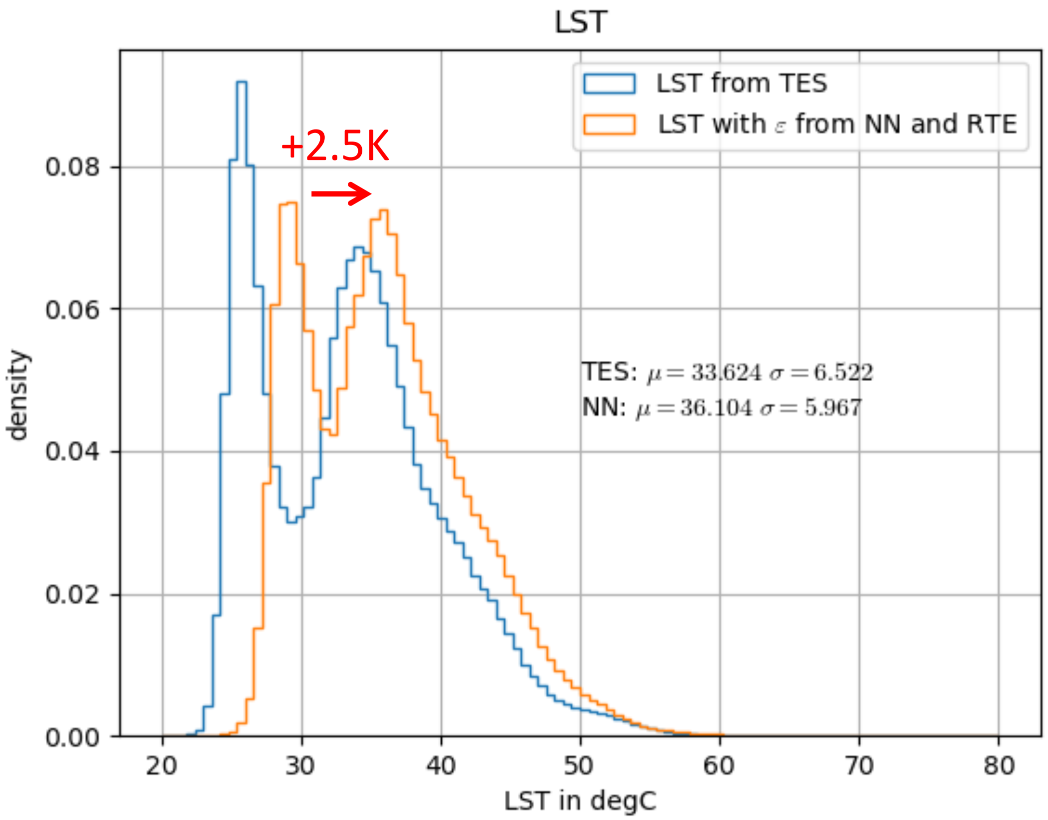
*LUMA Spectral Database (open access)

Note : MMD relation with urban material seem less linear !

Distribution of image LST: NN vs. TES after adding urban material







- Low impact on LST estimation
- No main change in TES results (MMD relation close)
- Determination of LSE Urban materials appear with NN

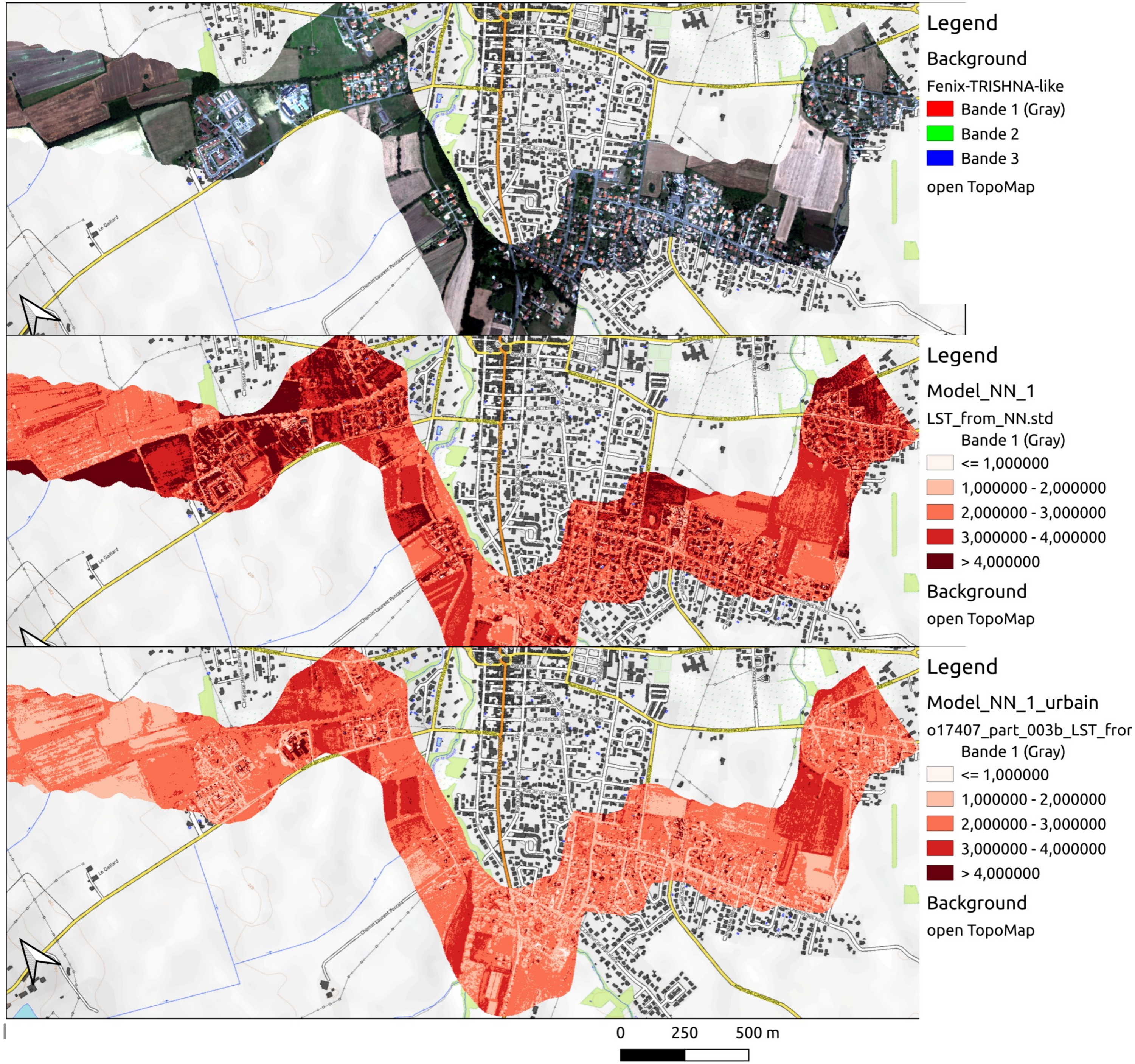
NN LST/LSE validity through std($LST_{i,NN}$)

The less the std($LST_{i,NN}$) is, the closest the LSE_i are to the realistic solution

from spectral database based on vegetation only

with urban made in addition

Convergence of $LST_{i,NN}$
= Improuvement !!
= accuracy in $LSE_{i,NN}$ value



Conclusion

- Present conclusions need validation !
- **There is a way for machine/data learning approach** to be more flexible and precise in LST / LSE determination ?
  - Reflectances inputs could be any optical sensor: S2, Landsat, ...

Need improvements !

- **Increase learning database** => more genericity / avoid extrapolation
- **Increase in situ measurement** => specific spectrum, CAL/VAL etc...
- Evaluate MMD relation impact on LST estimation
- Add/Need convergence approach of LSE solutions with NN to solve unique LST problem

way of DirectTES?

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Thank You !

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