

Direction de la Météorologie Nationale

Spatial Interpolation of Meteorological Data for crop forecasting: AURELHY

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Outlines

- Origin and theoretical background
- Implementation for Morocco
- Aurelhy : Adaptation to crop yield forecasting
- Perspectives and summary

AURELHY: Origin

- AURELHY: <u>A</u>nalyse <u>U</u>tilisant le <u>RE</u>Lief pour les besoins de l'<u>Hy</u>drométéorologie
- Authors: (Patrick Bénichou and Odile Le Breton, 1986) from METEO FRANCE

Aurelhy: Basic Idea

 Use of topography to guide the spatial interpolation of climatic variables (precipitation and others)



$P(Si) = P(xi, yi, Ri) = f(Ri) + \varepsilon(xi, yi)$

AURELHY: Suitability

- More suitable for the interpolation of means, deciles, and other Monthly statistics of long time series
- Suitable for precipitation, number of rainy days, temperature (max, min, no. of frost days...)

Sources: Bénichou and Le Breton, 1986; Ecole nationale de la météorologie, without date; Regimbeau, 2008

Topography effect on Moroccan climate

- W/E Gradient
- N/S Gradient
- Sea Effect
- Mountain Barrier



AURELHY: Steps involved

Terrain analysis

- Mapping relative altitude differences of smoothed local topographies
- PCA of local topography variables
- Regression of climate variable against terrain
- Surface predicted by regression
- Spatial interpolation of residuals by Kriging
- Adding surface of interpolated residuals to surface predicted by regression

Terrain analysis: New geometry adopted

★ The landscape variables correspond to the difference in elevation between each grid point and neighbors points regularly distributed around the grid point (8 sectors and 5 distances from 6 to 26 km.



Terrain analysis: PCA of Local Topography variables



From left to right respectively Pc1 to Pc10

Terrain analysis: 10 Pcs explain more than 92% of total variance



Terrain analysis: straightforward interpretation as terrain form



Source: Huard, 1990

Regression Issues: Predictors

Variable	Observations	Minimum	Maximum	Mean	Std. deviation
Х	47	-17.088	2.246	-6.392	4.508
у	47	19.412	36.329	31.584	4.316
Z	47	1.000	1494.000	427.596	447.693
seadist	47	7.517	817.026	124.748	156.043
PC1	47	-3489.414	1667.763	260.993	763.855
PC2	47	-918.187	2029.593	298.656	592.849
PC3	47	-770.923	800.999	-22.698	336.256
PC4	47	-295.293	705.233	100.296	210.094
PC5	47	-324.262	690.799	75.871	159.035
PC6	47	-630.096	489.101	-0.737	205.595
PC7	47	-284.001	403.841	5.757	126.310
PC8	47	-367.884	311.565	-6.073	125.335
PC9	47	-480.227	203.080	3.933	120.388
PC10	47	-421.230	258.358	2.755	108.250

Table 1: Description of predictors

Regression Issues: Co linearity

Variables	X	у	Z	seadist	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10
X	1	0.771	0.478	0.194	-0.068	0.076	0.230	0.197	0.227	0.178	0.107	-0.242	-0.005	0.135
у	0.771	1	0.162	-0.335	0.092	0.228	0.217	0.290	0.192	0.108	0.121	-0.234	-0.047	0.152
Z	0.478	0.162	1	0.455	-0.093	0.088	-0.016	0.054	0.084	0.016	0.242	-0.239	-0.176	-0.173
seadist	0.194	-0.335	0.455	1	0.018	-0.102	-0.096	-0.043	-0.207	0.008	-0.042	0.051	-0.063	-0.182
PC1	-0.068	0.092	-0.093	0.018	1	0.595	0.123	0.381	-0.354	-0.325	-0.315	-0.002	-0.305	-0.237
PC2	0.076	0.228	0.088	-0.102	0.595	1	0.085	0.354	0.158	0.051	-0.059	-0.207	-0.458	-0.235
PC3	0.230	0.217	-0.016	-0.096	0.123	0.085	1	0.111	-0.079	-0.271	0.092	-0.326	-0.083	0.031
DC4	0.407	0.000	0.054	0.040	0.004	0.054		4	0.004	0.404	0.045	0.050	0 070	0.004
PC4	0.197	0. 2 90	0.054	-0.043	0.381	0.354	0.111	1	0.224	0.134	-0.015	-0.053	-0.070	-0.081
PC5	0.227	0.192	0.084	-0.207	-0.354	0.158	-0.079	0.224	1	0.431	0.135	0.132	0.285	0.197
PC6	0.178	0.108	0.016	0.008	-0.325	0.051	-0.271	0.134	0.431	1	-0.174	0.337	0.237	0.209
PC7	0.107	0.121	0.242	-0.042	-0.315	-0.059	0.092	-0.015	0.135	-0.174	1	-0.397	-0.237	-0.095
PC8	-0.242	-0.234	-0.239	0.051	-0.002	-0.207	-0.326	-0.053	0.132	0.337	-0.397	1	0.491	0.182
PC9	-0.005	-0.047	-0.176	-0.063	-0.305	-0.458	-0.083	-0.070	0.285	0.237	-0.237	0.491	1	0.768
PC10	0.135	0.152	-0.173	-0.182	-0.237	-0.235	0.031	-0.081	0.197	0.209	-0.095	0.182	0.768	1

Table 2 Correlation matrix Between predictors Values in bold are different from 0 with a significance level alpha=0.05

Regression Issues: Multi Co Linearity



Figure 1-a: R2 between predictors

Figure 1-a: VIF

Regression Issues: Avoiding Multi Co linearity

- Use of Stepwise Regression : Backward and Forward elimination
- Reduction of predictors number
- Ensuring The significance of regression Coefficients
- Ensuring The normality of residuals which is an important condition for kriging

Residuals kriging

- Compute regression residues and spatially interpolate them with a kriging algorithm to a resolution of 0.1 degree:
- Detrend the quadratic drift from regression residues;
- Interpolate the detrended term with an ordinary Kriging using a spherical semivariogram;



Final mapping

Final mapping by addition of :
— Grid predicted by regression

 Grid obtained through kriging of residuals



AURELHY Implementation: R package

- R Version(>= 2.10.0)
- Dependents R Package: stats, graphics, shapefiles, gstat, Mass
- Author: Philippe Grosjean
- Download: http://r-forge.r-project.org/projects/aurelhy/

AURELHY R package: Utilities

- DEM Resampling to 0.1°
- Local Topography components
- SEA Distance Calculation
- Principal Component Analysis of Local Topography components
- FITTING Variogram

Data Needed: DEM and geo referenced Data records



comparison of Two variants of Aurelhy

• Variant 1:

Regression of each decadal climatic variable against PCs and kriging residuals

• Variant 2:

Regression of long term average of climatic variable and kriging differences

comparison of Two variants of Aurelhy (Rain)



comparison of Two variants of Aurelhy (Tmax)



comparison of Two variants of Aurelhy (Tmin)



Regression Residuals analysis (Tmin)



- <u>Regressions in using long term average gives</u> <u>significant models but generates more Fields</u> <u>not following a normal distribution.</u>
- GOOD REGRESSIONS BUT VERY LIKELY BAD KRIGING

leave one out Cross Validation (Temperatures)

<u>Both Variants Presents good and similar</u> results for Temperatures (Tmax and Tmin)

Variable	Variants	R ² adj	Slope	MSE
Tmin	Variant 1	0.95	0.951	2.23
	Variant 2	0.93	0.9	2.16
Tmax	Variant 1	0.92	0.998	7.32
ΠΙάλ	Variant 2	0.91	0.996	7.21

leave one out Cross Validation (Rainfall)

Rainfall: Variant 2 is more stable

	STANDART DEVIATION OF ERRORS			
	Variant1	Variant2		
MEAN	1.06E+14	16.9		
MINIMUM	5.01	4.4		
MAXIMUM	5.03E+15	264.24		

leave one out sensitivity



Role of interpolation in CGMS level 1



Daily Data needed for feeding CGMS

maximum temperature (°C) minimum temperature (°C) mean daily vapour pressure (hPa) mean daily windspeed at 10m (m/s) mean daily rainfall (mm) Penman potential evaporation from a free water surface (mm/day) Penman potential evaporation from a moist bare soil surface (mm/day) Penman potential transpiration from a crop canopy (mm/day) daily global radiation in KJ/m²/day daily mean snow depth in cm

Alternative entry for grid weather data

• CGM Version 9.2:

- Integration of Decadal grids of temperatures , rainfalls and number of rainy days by decade or month;
- 2. Downscaling to Daily time step

Pseudo Penman Formula for ETO Calculation



Figure 2.05: Spatial variations of the ratio between Penman-Monteith and Hargreaves estimations of evapotranspiration.

Summary

- Aurelhy has the potential to integrate the effect of topography for Tmin and Tmax interpolation at 10 days scale. Both variants are reliable.
- Using Long term average for precipitations gives stable results.
- Interpolation by Aurelhy needs more development especially for punctual/convective rain events.
- Aurelhy is sensitive to the number of stations and their geographic position
- Aurelhy is sensitive to Data quality and Data missing

Aurelhy Perspectives for CGMS

Generating decadal grids of Tmax, Tmin, Rain and number of rainy days;

• Using the calibrated Hargreaves formula for ETO;

THANK YOU!