Applied Time Series Analysis
FS 2012 – Week 11

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Multivariate Time Series Analysis

Idea: Infer the relation between two time series $X_1 = (X_{1,t})$ and $X_2 = (X_{2,t})$.

What is the difference to time series regression?

- Here, the two series arise „on an equal footing“, and we are interested in the correlation between them.
- In time series regression, the two (or more) series are causally related and we are interested in inferring that relation. There is an independent and several dependent variables.
- The difference is comparable to the difference between correlation and regression.

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Example: Permafrost Boreholes

A collaboration between the Swiss Institute for Snow and Avalanche Research with the Zurich University of Applied Sciences:

Evelyn Zenklusen Mutter & Marcel Dettling

Example: Permafrost Boreholes

- given is a bivariate time series with 2*92 observations
- 2 measurements were made everyday in summer 2006
- series 1: air temperature at Platthorn 3345m
- series 2: soil temperature at Hörnli hut 3295m

Goal of the analysis:

1) Answer whether changes in the air temperature are correlated with changes in the soil temperature.

2) If a correlation is present, what is the delay?

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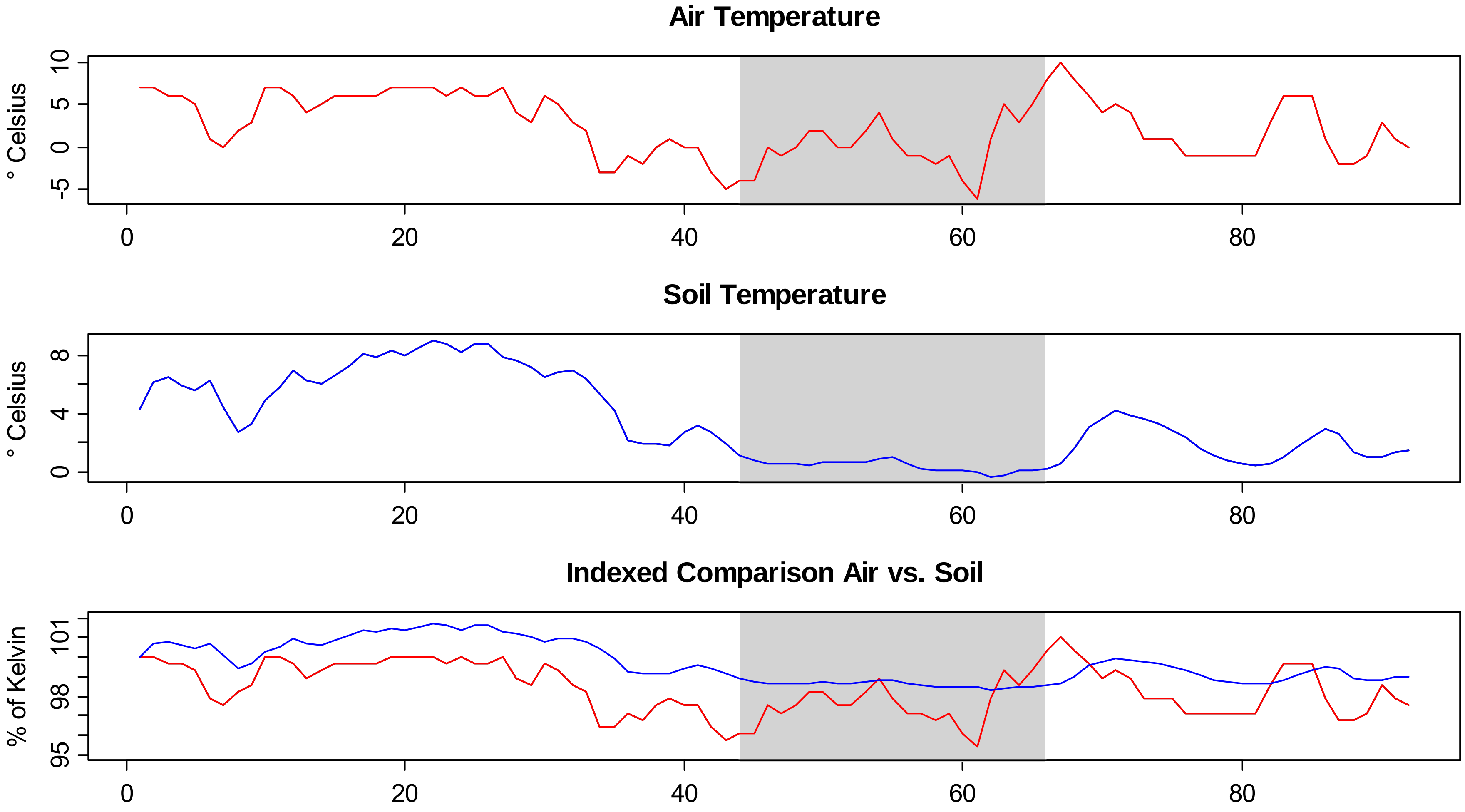
Air & Soil Temperature Comparison



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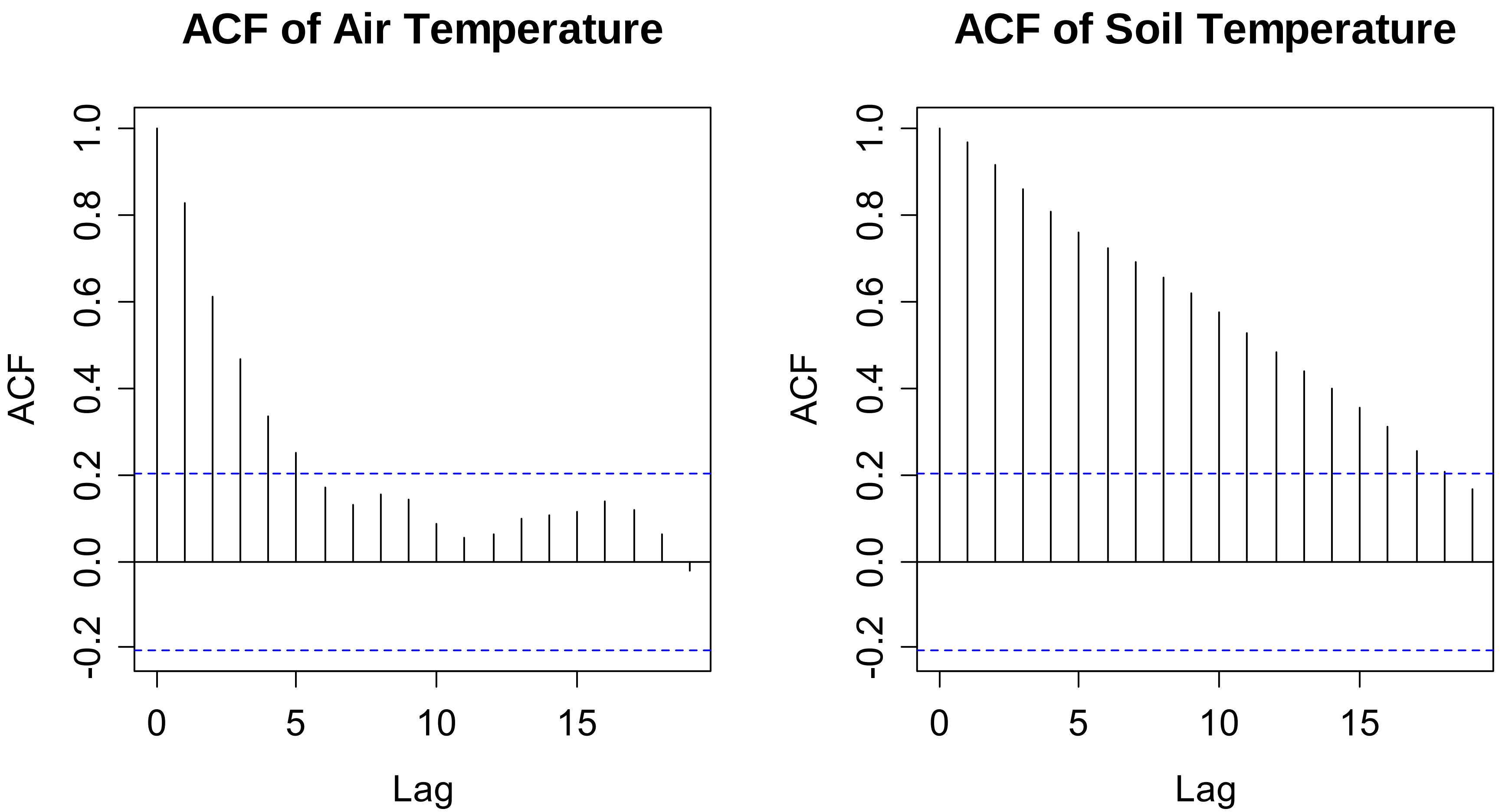
Are the Series Stationary?



How to Proceed?

1) The series seem to have „long memory“

2) Pure AR/MA/ARMA do not fit the data well

→ Differencing may help with this

Another advantage of taking differences:

→ we infer, whether there is a relation between the changes in the air temperatures, and the changes in the soil temperatures.

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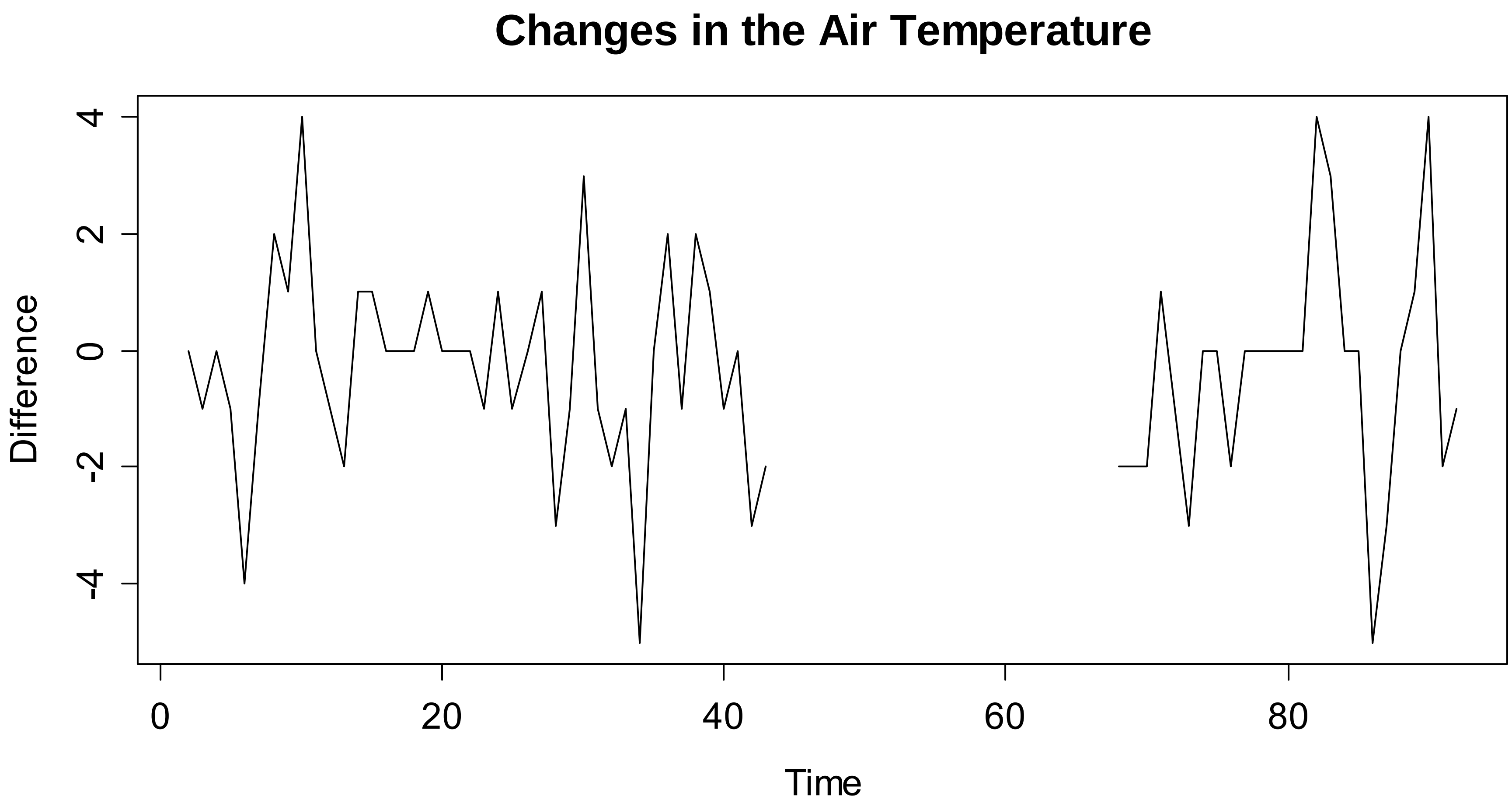
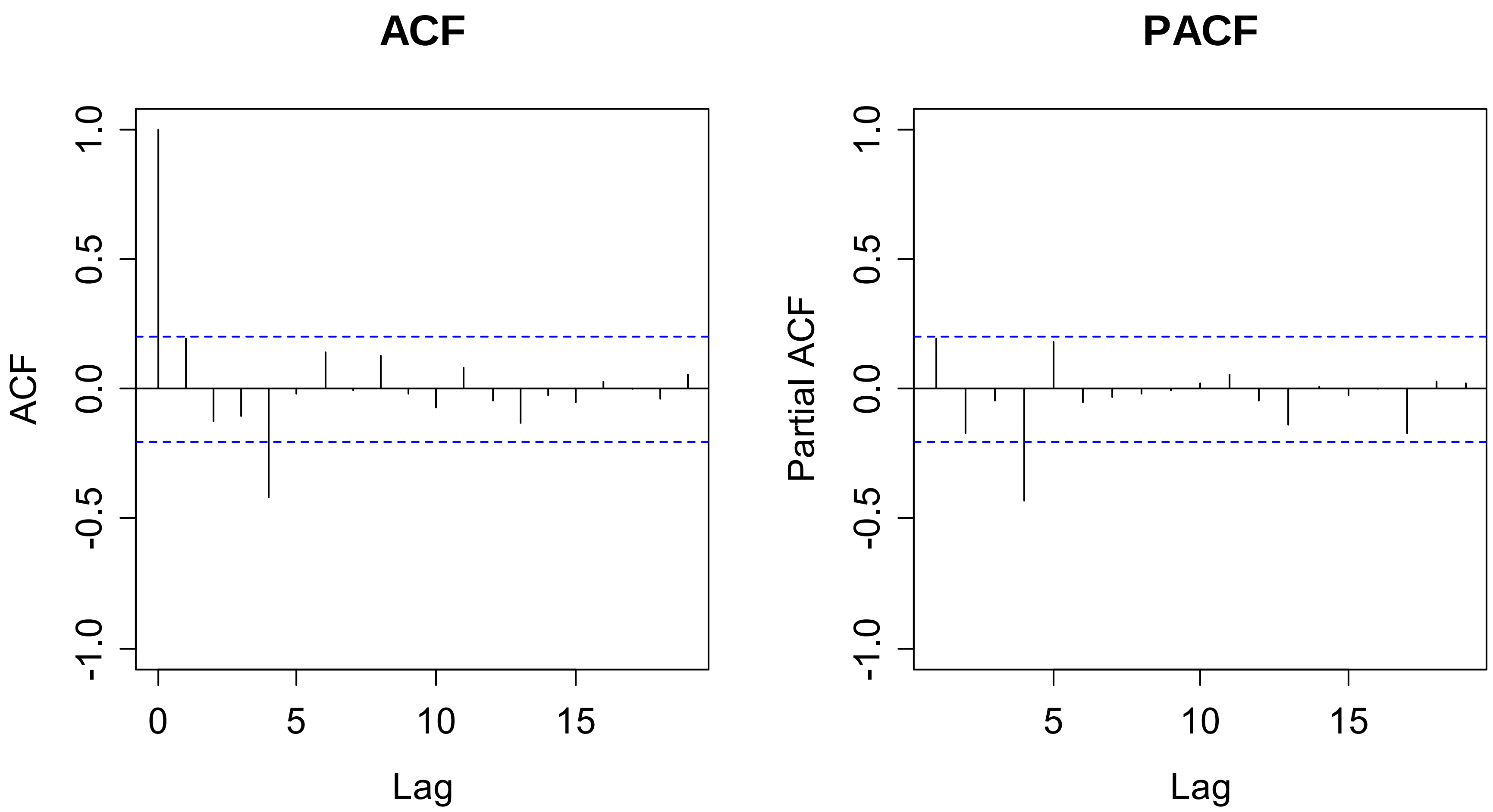
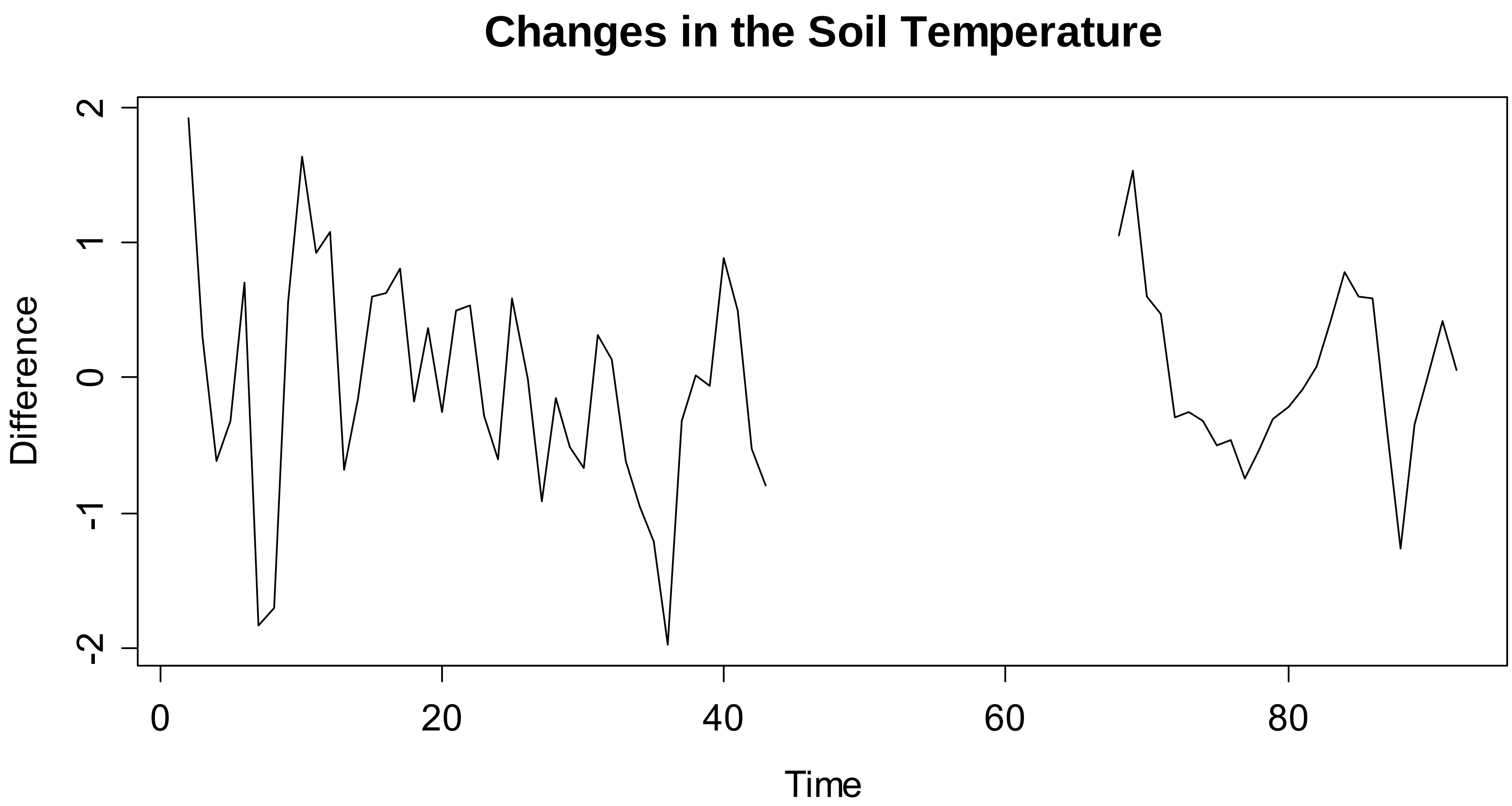
Changes in the Air Temperature



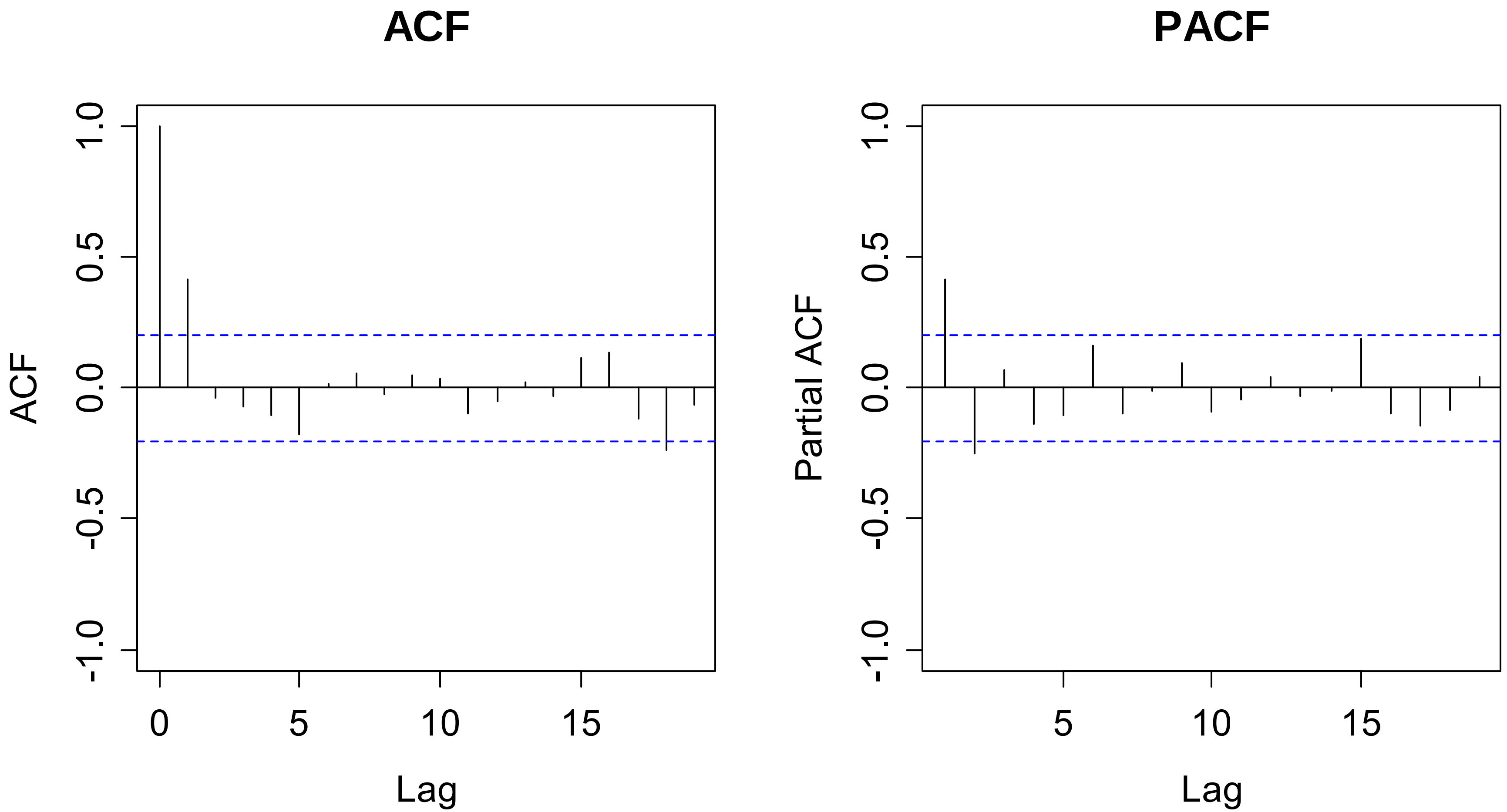
ACF/PACF for Air Temperature Changes



Changes in the Soil Temperature



ACF/PACF for Soil Temperature Changes



Cross Covariance

The cross correlations describe the relation between two time series. However, note that the interpretation is quite tricky!

$$\left.\begin{aligned}\gamma_{11}(k) &= Cov(X_{1,t+k}, X_{1,t}) \\ \gamma_{22}(k) &= Cov(X_{2,t+k}, X_{2,t})\end{aligned}\right\}$$

usual „within series“ covariance

$$\left.\begin{aligned}\gamma_{12}(k) &= Cov(X_{1,t+k}, X_{2,t}) \\ \gamma_{21}(k) &= Cov(X_{2,t+k}, X_{1,t})\end{aligned}\right\}$$

cross covariance, independent from t

Also, we have: $\gamma_{12}(-k) = Cov(X_{1,t-k}, X_{2,t}) = Cov(X_{2,t+k}, X_{1,t}) = \gamma_{21}(k)$

Cross Correlations

It suffices to analyze $\gamma_{12}(k)$, and neglect $\gamma_{21}(k)$, but we have to regard both positive and negative lags k.

We again prefer to work with correlations:

$$\rho_{12}(k) = \frac{\gamma_{12}(k)}{\sqrt{\gamma_{11}(0)\gamma_{22}(0)}}$$

which describe the linear relation between two values of X_1 and X_2, when the series X_1 is *k* time units ahead.

Estimation

Cross covariances and correlations are estimated as follows:

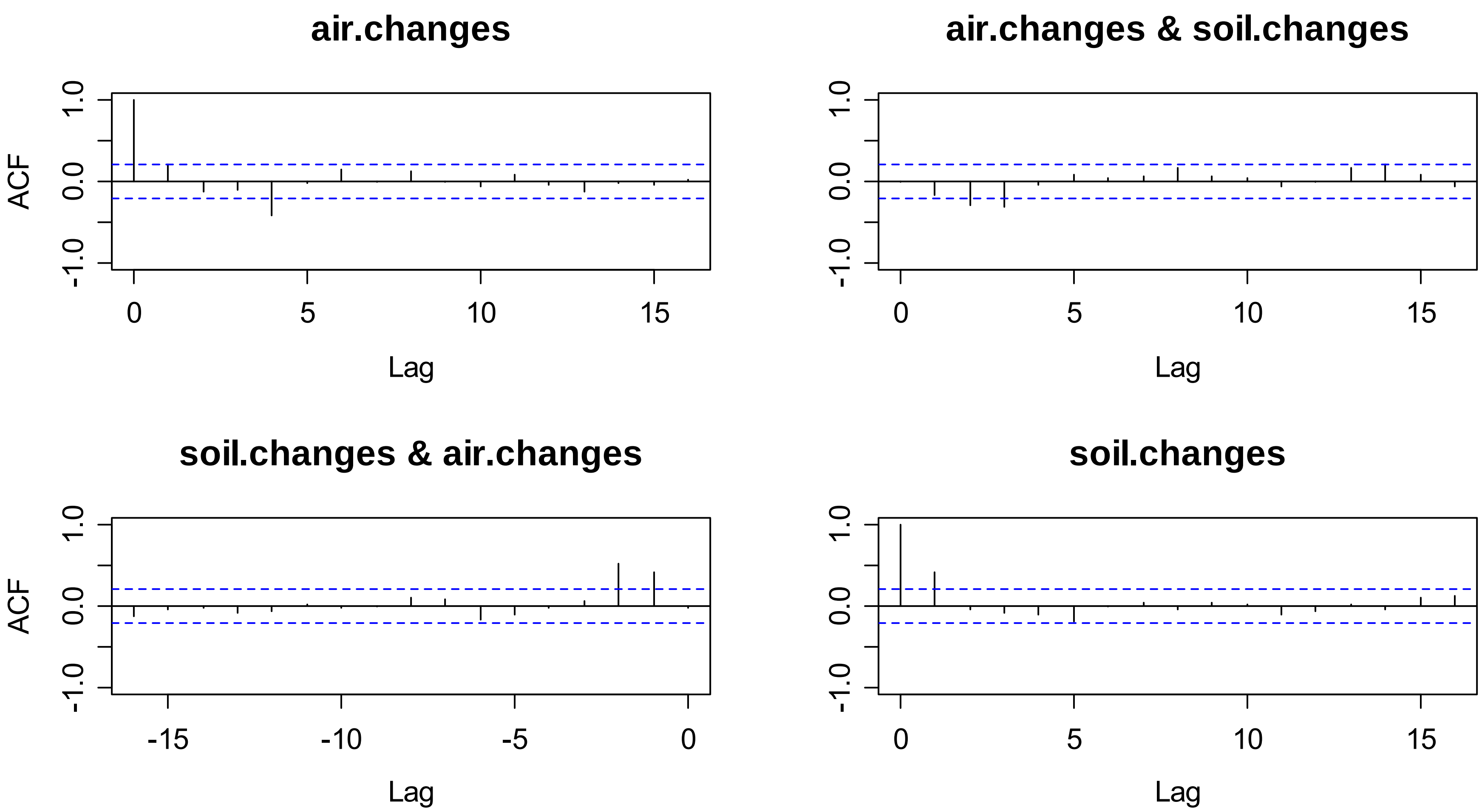
$$\hat{\gamma}_{12}(k) = \frac{1}{n}\sum_t (x_{1,t+k} - \overline{x}_1)(x_{2,t} - \overline{x}_2)$$

and

$$\hat{\rho}_{12}(k) = \frac{\hat{\gamma}_{12}(k)}{\sqrt{\hat{\gamma}_{11}(0)\hat{\gamma}_{22}(0)}}, \quad \text{respectively.}$$

The plot of $\hat{\rho}_{12}(k)$ versus the lag *k* is called the cross correlogram. It has to be inspected for both + and – *k*.

Sample Cross Correlation



Interpreting the Sample Cross Correlation

The confidence bounds in the sample cross correlation are only valid in some special cases, i.e. if there is no cross correlation and at least one of the series is uncorrelated.

Important: the confidence bounds are often too small!

For computing them, we need: $Var(\hat{\rho}_{12}(k))$

This is a difficult problem. We are going to discuss a few special cases and then show how the problem can be circumvented.

Special Case 1

We assume that there is no cross correlation for large lags k:

If $\rho_{12}(j) = 0$ for $|j| \geq m$, we have for $|k| \geq m$:

$$Var(\hat{\rho}_{12}(k)) \approx \frac{1}{n} \sum_{j=-\infty}^{\infty} \left(\rho_{11}(j)\rho_{22}(j) + \rho_{12}(j+k)\rho_{12}(j-k) \right)$$

This goes to zero for large k and we thus have consistency. For giving statements about the confidence bounds, we would have to know more about the cross correlations, though.

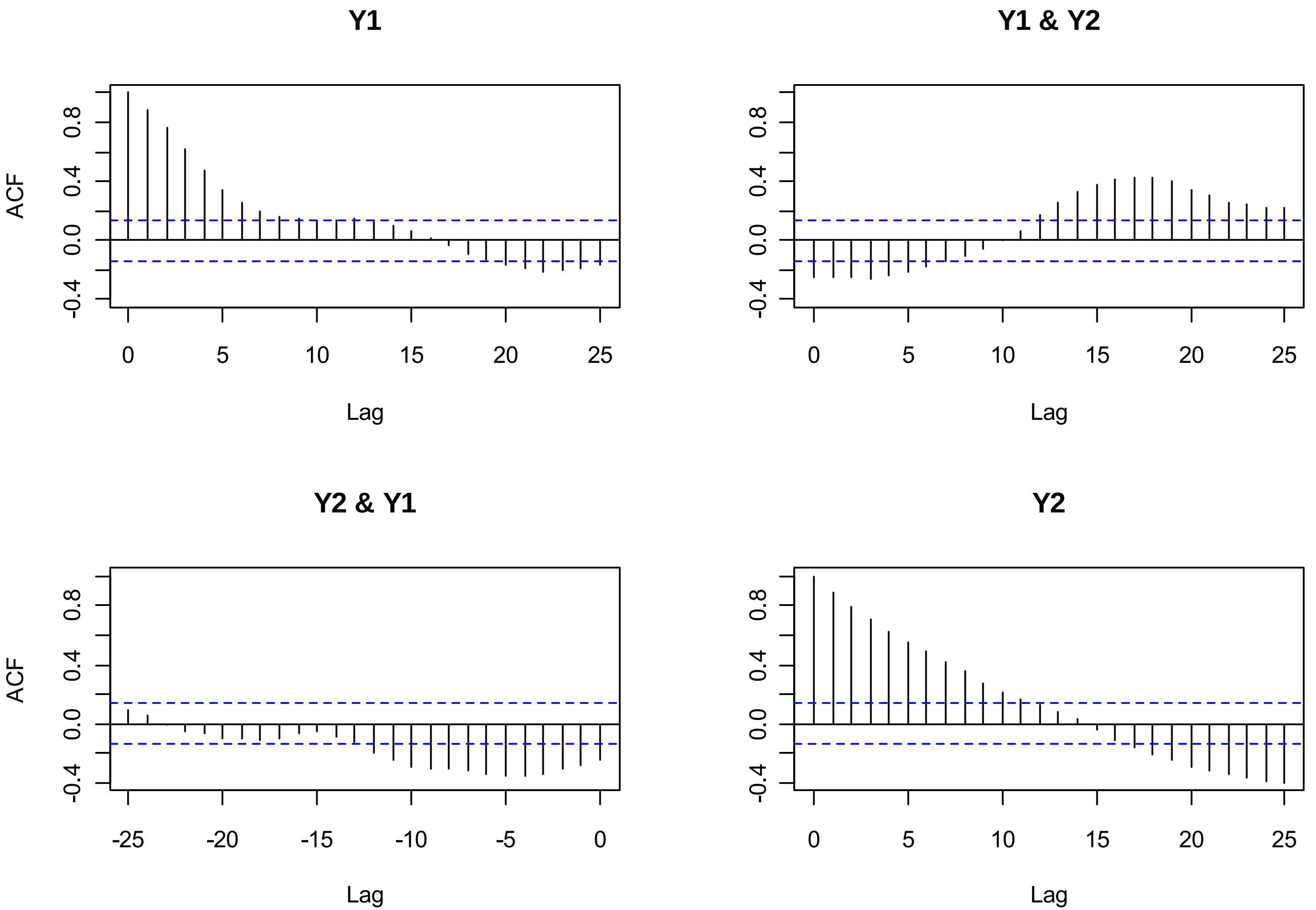
Special Case 2

There is no cross correlation, but X_1 and X_2 are time series that show correlation „within“:

$$Var(\hat{\rho}_{12}(k)) \approx \frac{1}{n} \sum_{j=-\infty}^{\infty} \rho_{11}(j)\rho_{22}(j)$$

See the blackboard… for the important example showing that the cross correlation estimations can be arbitrarily bad!

Special Case 2: Simulation Example



Special Case 3

There is no cross correlation, and X_1 is a white noise series that is independent from X_2. Then, the estimation variance simplifies to:

$$Var(\hat{\rho}_{12}(k)) \approx \frac{1}{n}$$

Thus, the confidence bounds are valid in this case.

However, we introduced the concept of cross correlation to infer the relation between correlated series. The trick of the so-called „prewhitening“ helps.

Prewhitening

Prewhitening means that the time series is transformed such that it becomes a white noise process, i.e. is uncorrelated.

We assume that both stationary processes X_1 and X_2 can be rewritten as follows:

$$U_t = \sum_{i=0}^{\infty} a_i X_{1,t-i} \quad \text{and} \quad V_t = \sum_{i=0}^{\infty} b_i X_{2,t-i},$$

with uncorrelated U_t and V_t. Note that this is possible for ARMA(p,q) processes by writing them as an AR(∞). The left hand side of the equation then is the innovation.

Cross Correlation of Prewhitened Series

The cross correlation between U_t and V_t can be derived from the one between $X_{1,t}$ and $X_{2,t}$:

$$\rho_{UV}(k) = \sum_{j=0}^{\infty} \sum_{j=0}^{\infty} a_i b_i \rho_{X_1 X_2}(k+i-j)$$

Thus we have:

$$\rho_{UV}(k) = 0 \quad \text{for all k} \quad \Leftrightarrow \quad \rho_{X_1 X_2}(k) = 0 \quad \text{for all k}$$

Now: generate U,V, estimate cross correlations and, by using the confidence bands, check whether they are signficant

Simulation Example

Since we are dealing with simulated series, we know that:

$$X_{i,t} = 0.9 \cdot X_{i,t-1} + E_t \text{, thus} \quad E_t = X_{i,t} - 0.9 \cdot X_{i,t-1}$$

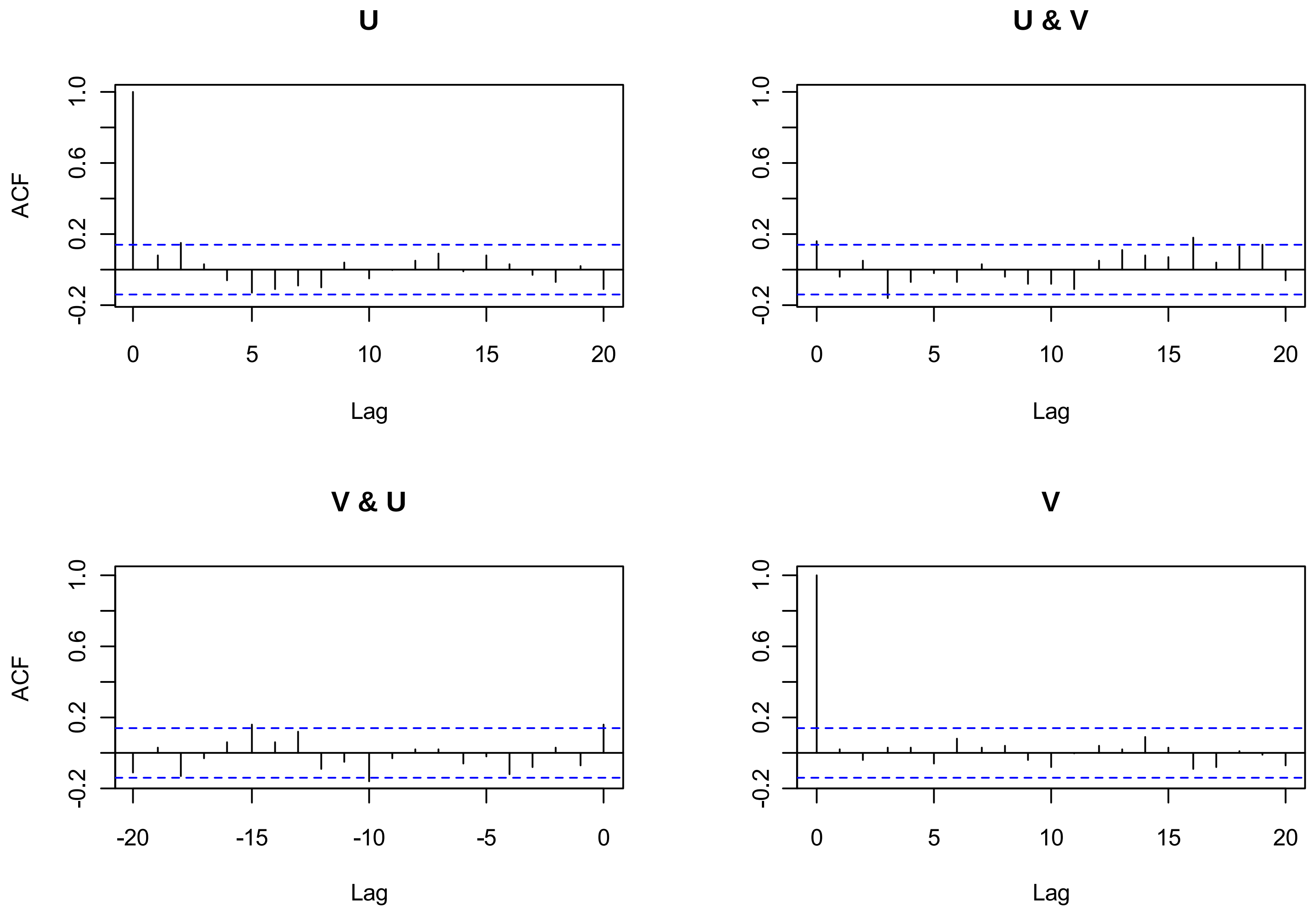
In practice, we don‘t know the AR-coefficients, but plug-in the respective estimates:

$$U_t = X_{1,t} - \hat{\alpha}_{1,1} X_{1,t-1} \quad \text{with} \quad \hat{\alpha}_{1,1} = 0.911$$

$$V_t = X_{2,t} - \hat{\alpha}_{2,1} X_{2,t-1} \quad \text{with} \quad \hat{\alpha}_{2,1} = 0.822$$

We will now analyse the sample cross correlation of U_t and V_t, which will also allow to draw conclusions about X_1 and X_2.

Cross Correlation in the Simulation Example



Cross Correlation in the Simulation Example

We observe that:

- U_t and V_t are white noise processes
- There are no (strongly) significant cross correlations

We conjecture that:

- X_1 and X_2 are not cross correlated either.

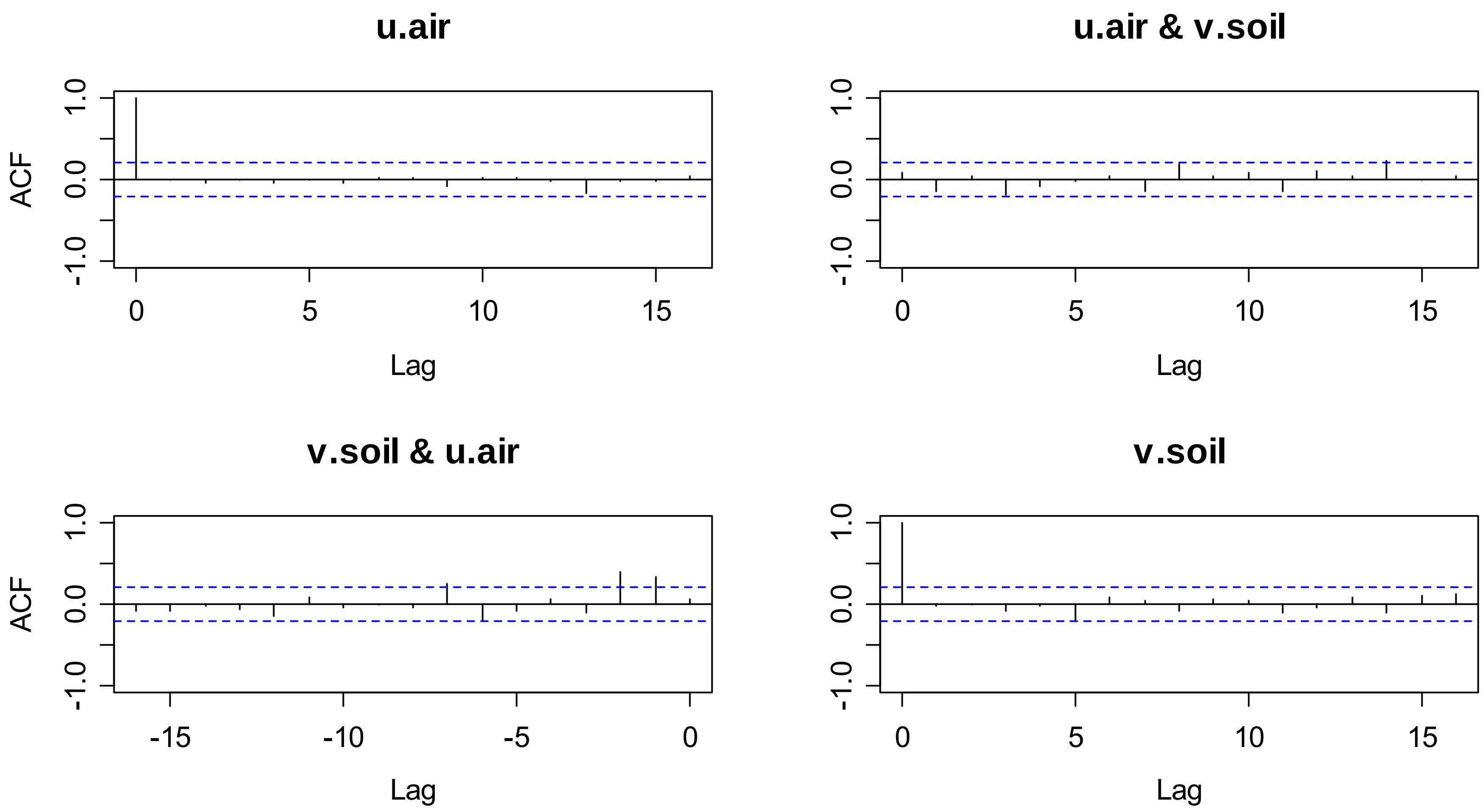
→ This matches our „expectations", or better, true process.

Prewhitening the Borehole Data

What to do:

- ARMA(p,q)-models are fitted to the differenced series
- Best choice: AR(5) for the air temperature differences
  MA(1) for the soil temperature differences
- The residual time series are U_t and V_t, white noise
- Check the sample cross correlation (see next slide)
- Model the output as a linear combination of past input values: transfer function model.

Prewhitening the Borehole Data



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Transfer Function Models

Properties:

- Transfer function models are an option to describe the dependency between two time series.

- The first (input) series influences the second (output) one, but there is no feedback from output to input.

- The influence from input to output only goes „forward“.

The model is:

$$X_{2,t} - \mu_2 = \sum_{j=0}^{\infty} \nu_j (X_{1,t-j} - \mu_1) + E_t$$

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Transfer Function Models

The model is:

$$X_{2,t} - \mu_2 = \sum_{j=0}^{\infty} \nu_j (X_{1,t-j} - \mu_1) + E_t$$

- $E[E_t]=0$.
- E_t and $X_{1,s}$ are uncorrelated for all t and s.
- E_t and E_s are usually correlated.
- For simplicity of notation, we here assume that the series have been mean centered.

Cross Covariance

When plugging-in, we obtain for the cross covariance:

$$\gamma_{21}(k) = Cov(X_{2,t+k}, X_{1,t}) = Cov\left(\sum_{j=0}^{\infty} \nu_j X_{1,t+k-j}, X_{1,t} \right) = \sum_{j=0}^{\infty} \nu_j \gamma_{11}(k-j)$$

- If only finitely many coefficients are different from zero, we could generate a linear equation system, plug-in $\hat{\gamma}_{11}$ and $\hat{\gamma}_{21}$ to obtain the estimates $\hat{\nu}_j$.

→ **This is not a statistically efficient estimation method.**

Special Case: $X_{1,t}$ Uncorrelated

If $X_{1,t}$ was an uncorrelated series, we would obtain the coefficients of the transfer function model quite easily:

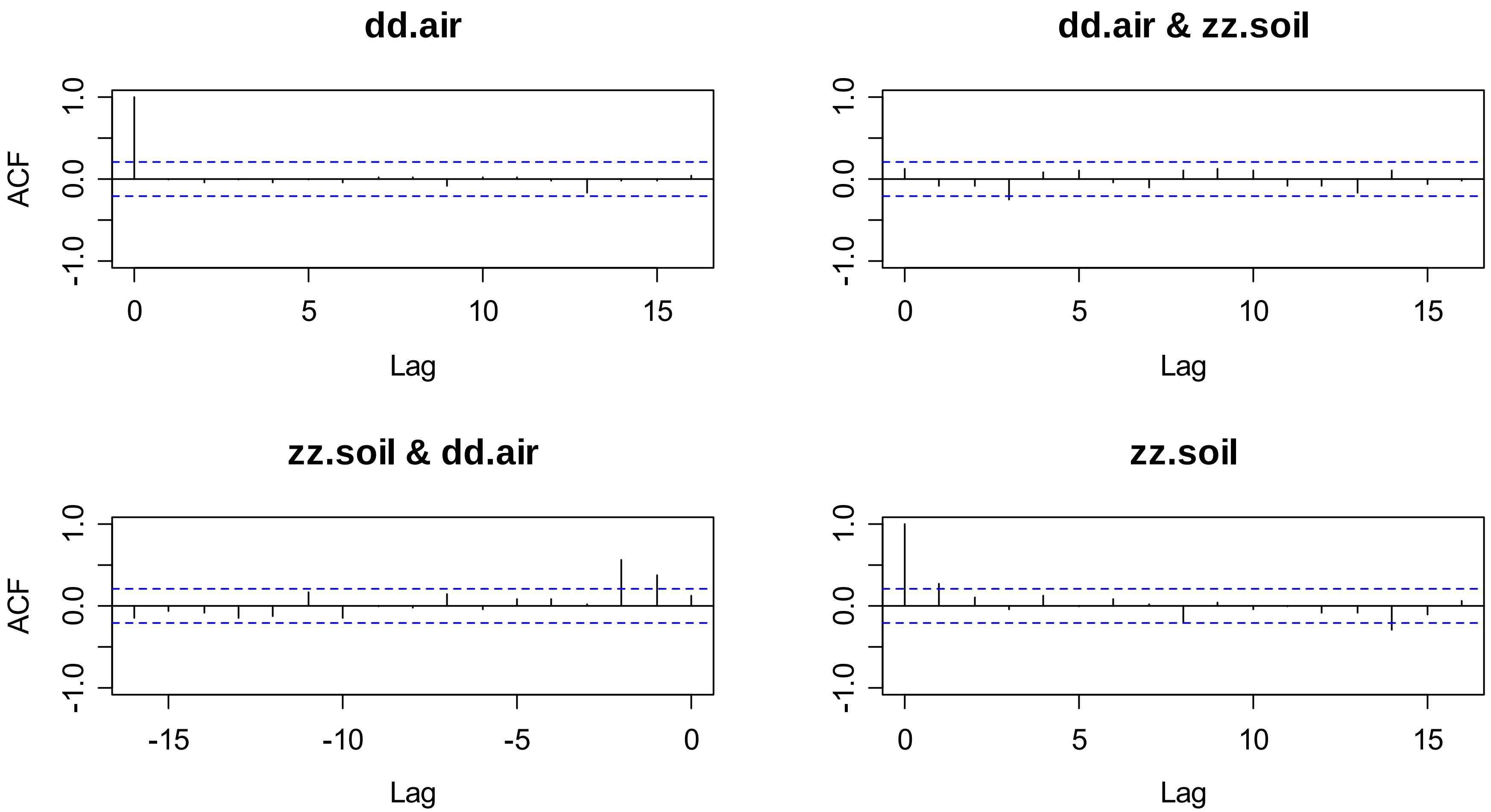
$$\nu_k = \frac{\gamma_{21}(k)}{\gamma_{11}(0)}$$

However, this is usually not the case. We can then:

- transform all series in a clever way
- the transfer function model has identical coefficients
- the new, transformed input series is uncorrelated

→ see blackboard for the transformation

Borehole Transformed



Borehole: Final Remarks

- In the previous slide, we see the empirical cross correlations $\hat{\rho}_{21}(k)$ of the two series D_t and Z_t.
- The coefficients $\hat{v}_k$ from the transfer function model will be proportional to the empirical cross correlations. We can already now conjecture that the output is delayed by 1-2 days.
- The formula for the transfer function model coefficients is:

$$\hat{v}_k = \frac{\hat{\sigma}_Z}{\hat{\sigma}_D} \hat{\rho}_{21}(k)$$

Borehole: R-Code and Results

```
> dd.air  <- resid(fit.air)
> coefs   <- coef(fit.air)[1:5])
> zz.soil <- filter(diff(soil.na), c(1, -coefs, sides=1)
> as.int  <- ts.intersect(dd.air, zz.soil)
> acf.val <- acf(as.int, na.action=na.pass)
```

Transfer Function Model Coefficients:

```
> multip  <- sd(zz.soil, na.rm=..)/sd(dd.air, na.rm=..)
> multip*acf.val$acf[,2,1]
 [1]  0.054305137  0.165729551  0.250648114  0.008416697
 [5]  0.036091971  0.042582917 -0.014780751  0.065008411
 [9] -0.002900099 -0.001487220 -0.062670672  0.073479065
[13] -0.049352348 -0.060899602 -0.032943583 -0.025975790
[17] -0.057824007
```