

# TIME SERIES ANALYSIS FOR ENERGY DATA

### M6 - Seasonal ARIMA Models

Prof. Luana Medeiros Marangon Lima, Ph.D.

Nicholas School of the Environment - Duke University

### Learning goals

 $\square$  Discuss the seasonal ARIMA model – SARIMA

 $\Box$  Learn how to identify order of seasonal component

 $\square$  Learn how to fit SARIMA models in R

# Seasonal Models

### SARIMA

# Modeling with Seasonality

 $\square$  So far we have two ways to deal with seasonality

- Linear regression on seasonal dummy variables and work with residuals
- **n Computing and subtracting the average of each** "month" (season)
- $\square$  In R: use stats::decompose() and forecast::seasadj()

### □ Drawbacks

- **□** Need to add seasonality back after fitting the model
- **□** Seasonal component is modeled as "constant" over time

### Seasonal Models

- □ Today we will learn a new approach: work with seasonal models, i.e., models that can handle seasonal time series
- $\Box$  We still need to identify the seasonal component but we do not need to remove it from the series



 $\Box$  And we don't need to add it back after fitting the model

### Seasonal ARIMA Models

- □ The Seasonal ARIMA models rely on seasonal lags and difference to fit the seasonal pattern
- $\Box$  The seasonal part of the ARIMA model have three additional parameters

P: number of seasonal autoregressive terms D: number of seasonal differences Q: number of moving average terms

 $\Box$  The complete model is called an

 $ARIMA(p, d, q)\times (P, D, Q)$ 

Non-seasonal Seasonal part

part

### Seasonal ARIMA Models (cont'd)

- $\Box$  We have two terms that refer to differencing
- $\square$  How does all this differencing work?

$$
\begin{aligned}\nIf \ d &= 0, D = 1; \qquad y_t = Y_t - Y_{t-s} \\
If \ d &= 1, D = 1; \qquad y_t = (Y_t - Y_{t-1}) - (Y_{t-s} - Y_{t-s-1})\n\end{aligned}
$$

- $\Box$  Note that s is the seasonal period, i.e., for monthly data  $s = 12$
- $\Box$  D should never be more than 1
- $\Box$   $(d + D)$  should never be more than 2

### Seasonal ARIMA Models (cont'd)

 $\Box$  What about the seasonal AR and MA terms?

If  $P = 1$ :  $y_{t-s}$  is added to the equation If  $Q = 1$ :  $a_{t-s}$  is added to the equation

- $P$  ( $P$  +  $Q$ ) should not be more than one
- □ After differencing plot ACF and PACF

**□** Positive spikes in ACF at lag 12, 24, 36, ... and single positive spike in PACF at lag 12 **□** Negative spike in ACF at lag 12 and negative spikes in PACF at lag 12, 24, 36, …  $P=1$  $Q=1$ 

### Examples: Seasonal ARIMA

□ SARIMA(1,0,1)(1,0,0)<sub>[12]</sub>



### Periodic AR Model (PAR)

- $\Box$  Also known as PAR(p) where p is the order of autoregressive model
- $\Box$  Similar to having one AR model for each season of the year

$$
y_t = \phi_{1,s} y_{t-1} + \dots + \phi_{p,s} y_{t-p} + a_t
$$

- $\Box$  Note that  $s = 1,2,3,...$  depending on the number of seasons
- $\Box$  The autoregressive parameter vary with the season for lag



### ARIMA Models Summary

- $\Box$  AR(p), MA(q), ARMA(p,q) stationary and nonseasonal process
- □ ARIMA(p,d,q) non-stationary and non-seasonal process
	- **□** The Integrated part can handle the non-stationarity
	- The non-stationary could be either a deterministic or stochastic trend eliminated by differencing
- □ Seasonal ARIMA or SARIMA non-stationary and seasonal process **ARIMA**  $(p, d, q) \times (P, D, Q)$

Non-seasonal Seasonal part

# Fitting ARIMA Models

Cheat sheet

Start with non-seasonal part

- $\square$  Step 1: Run stationary test
	- To identify stochastic trend use ADF
	- **n** To identify determinist trend use Mann Kendall
- $\Box$  Step 2: If either trend is present  $d=1$ 
	- **n** It may be the case that you need differencing more than once to remove trend
	- $\blacksquare$  To find out if  $d=1$  is enough, run the tests again on the differenced series
	- **n** Repeat the process until there is no trend on data ( $d \le 2$ )
	- $\blacksquare$  There is a function in R that returns the number of differences needed to achieve stationary

ndiffs(x, alpha =  $0.05$ , test =  $c("kpss", "adf", "pp"), max.d = 2)$ 

### □ Step 3: Plot ACF and PACF and look the behavior of non-seasonal lags

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#### Move to seasonal component

### $\square$  Step 4: Check if seasonal differencing is needed

- Seasonality can usually be verified by plotting your time series or by spikes at equally spaced lags (multiples of  $\log s$ ) on ACF and PACF
- $\blacksquare$  If you are still not sure about the existence of seasonal component you can run statistical tests
- **□** The seasonal difference is needed if the seasonal pattern is strong and stable over time
- **□** There is also a function in R that returns the number of seasonal differences needed to achieve stationary

nsdiffs(x,  $m = frequency(x)$ , test = c("ocsb", "ch"),  $max.D = 1$ )

Move to seasonal component

□ Step 5: Again ACF and PACF plots but now look at the seasonal lags





Multiple spikes at seas. lag (SMA process) Single Spike (SAR process)

# Some Rules for ARIMA Modeling

- $\Box$  If the series have positive autocorrelations out to a high number of lags, then it probably needs differencing more than once
- $\Box$  If the lag-1 autocorrelation is zero or negative, or the autocorrelations are all small with no pattern, then the series does not need a higher order of differencing
- $\Box$  If the lag-1 autocorrelation is -0.5 or more negative, the series may be overdifferenced

# Some Rules for ARIMA Modeling

 $\square$  Never use more than 1 order of seasonal differencing  $D\leq 1$ 

- $\square$  Never use more than 2 orders of total differencing  $sead(D) + nonseasonal(d) \leq 2$
- $\Box$  If the autocorrelation at the seasonal period is positive, consider adding an **SAR** term to the model
- $\Box$  If the autocorrelation at the seasonal period is negative, consider adding an **SMA**
- $\Box$  Avoid mixing SAR and SMA terms in the same model, and avoid using more than one of either kind

 $P + Q \leq 1$ 

## The ndiffs() and nsdiffs() tests

#### **Augmented Dickey Fuller (ADF)**

Check for stochastic trend

 $\int H_0$ :  $\phi = 1$  (i.e. contain a unit root)  $H_1: \phi < 1$  (i.e. is stationary

#### **Kitawoski-Phillips-Schmidt-Shin (KPSS)**

Check for deterministic & stochastic trend

- $\int H_0$ : stationary around determinist trend
	- $H_1$ : contain a unit root

#### **Phillips-Perron test (PP)**

Check for stochastic trend

 $\int H_0$ :  $\phi = 1$  (i.e. contain a unit root)  $H_1: \phi < 1$  (i.e. is stationary

#### **Canova and Hansen (CH)**

Check for seasonal pattern

 $\int H_0$ : seasonal pattern is stable  $H_1$ : not stable.

#### **Osborn,. Chui, Smith and Birchenhall (OCSB)**

Check for seasonal unit root

- $\int H_0$ : seasonal unit root.
- $H_1$ : no seasonal unit root

# Covariates in ARIMA

ARIMAX model

# More on ARIMA and SARIMA in R

Constants in the model

### Constants in ARIMA models in R

- $\Box$  The function Arima() takes three arguments regarding constants
	- $\blacksquare$  include.mean only has effect when  $d=0$  and is true by default
	- include.drift allows  $\mu \neq 0$  when  $d = 1$  and is false by default
	- ¤ include.constant more general. If TRUE, will set include.mean=TRUE if  $d = 0$  and include.drift=TRUE if  $d = 1$
	- ¤ Note: For d>1 no constant is allowed
- $\Box$  The function auto.arima automates the inclusion of a constant
	- **□** If alllowdrift=FALSE is specified then the constant is only allowed when  $d = 0$
- $\Box$  The arima() function only has the include.mean option



# THANK YOU !

### luana.marangon.lima@duke.edu

Master of Environmental Management Program Nicholas School of the Environment - Duke University