CCFs, Differencing, & AR(1) models

Lecture 08

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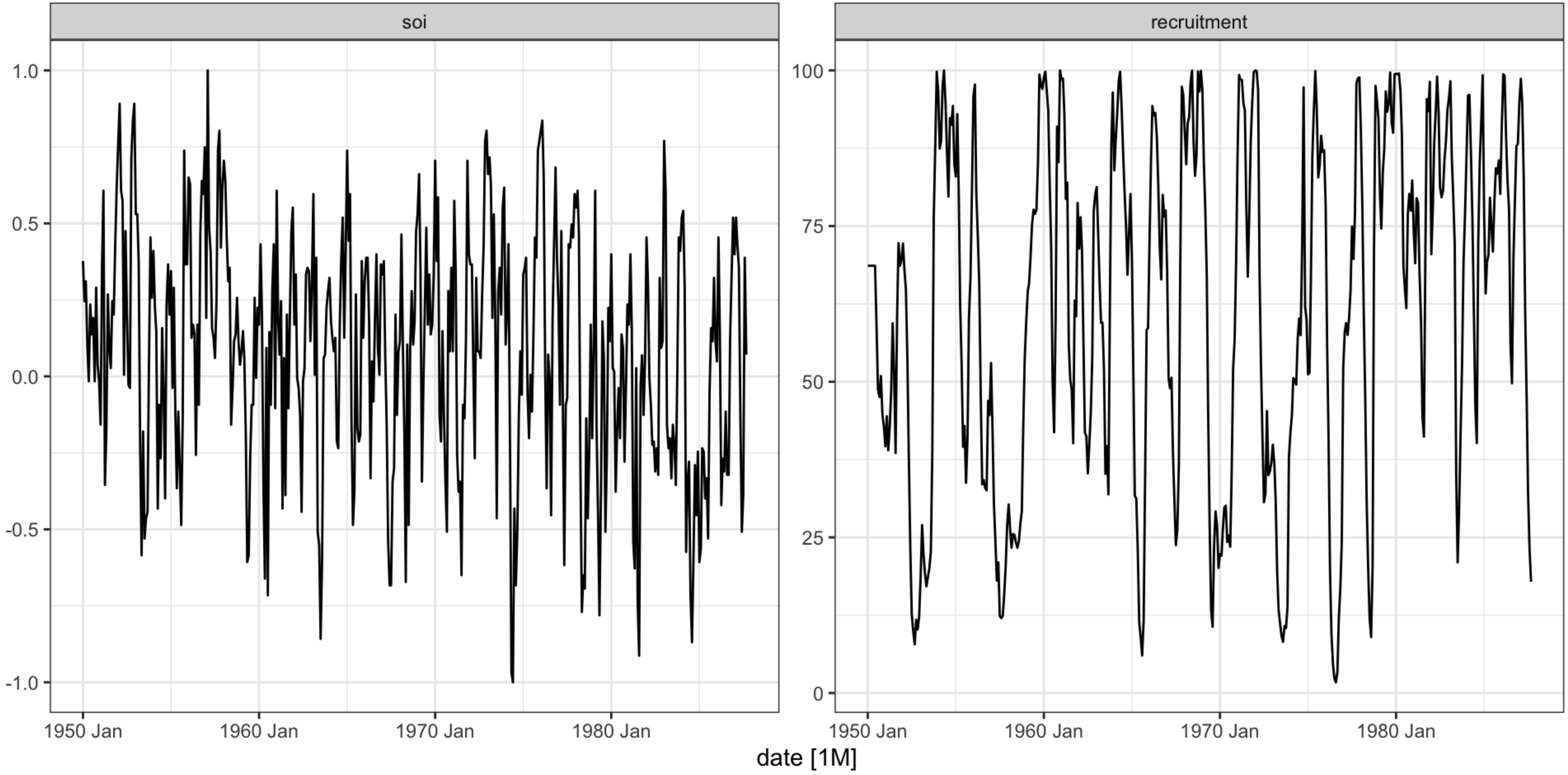
Lagged Predictors and CCFs

Southern Oscillation Index & Recruitment

The Southern Oscillation Index (SOI) is an indicator of the development and intensity of El Niño (negative SOI) or La Niña (positive SOI) events in the Pacific Ocean. These data also include the estimate of “recruitment”, which indicate fish population sizes in the southern hemisphere.

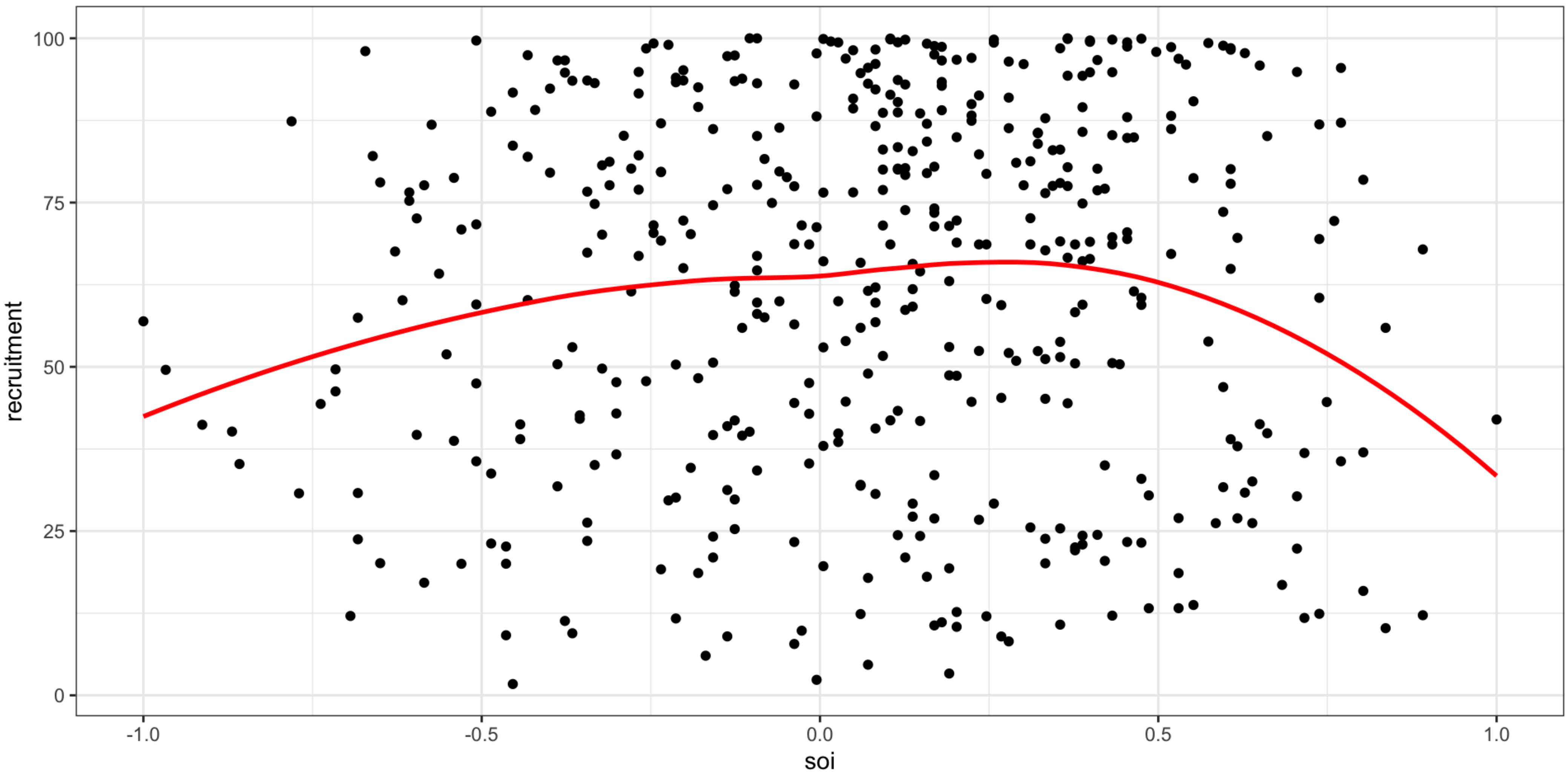
```
# A tsibble: 453 x 3 [1M]
       date    soi recruitment
      <mth>  <dbl>       <dbl>
 1 1950 Jan  0.377        68.6
 2 1950 Feb  0.246        68.6
 3 1950 Mar  0.311        68.6
 4 1950 Apr  0.104        68.6
 5 1950 May -0.016        68.6
 6 1950 Jun  0.235        68.6
 7 1950 Jul  0.137        59.2
 8 1950 Aug  0.191        48.7
 9 1950 Sep -0.016        47.5
10 1950 Oct  0.29         50.9
# ℹ 443 more rows
```

Time series



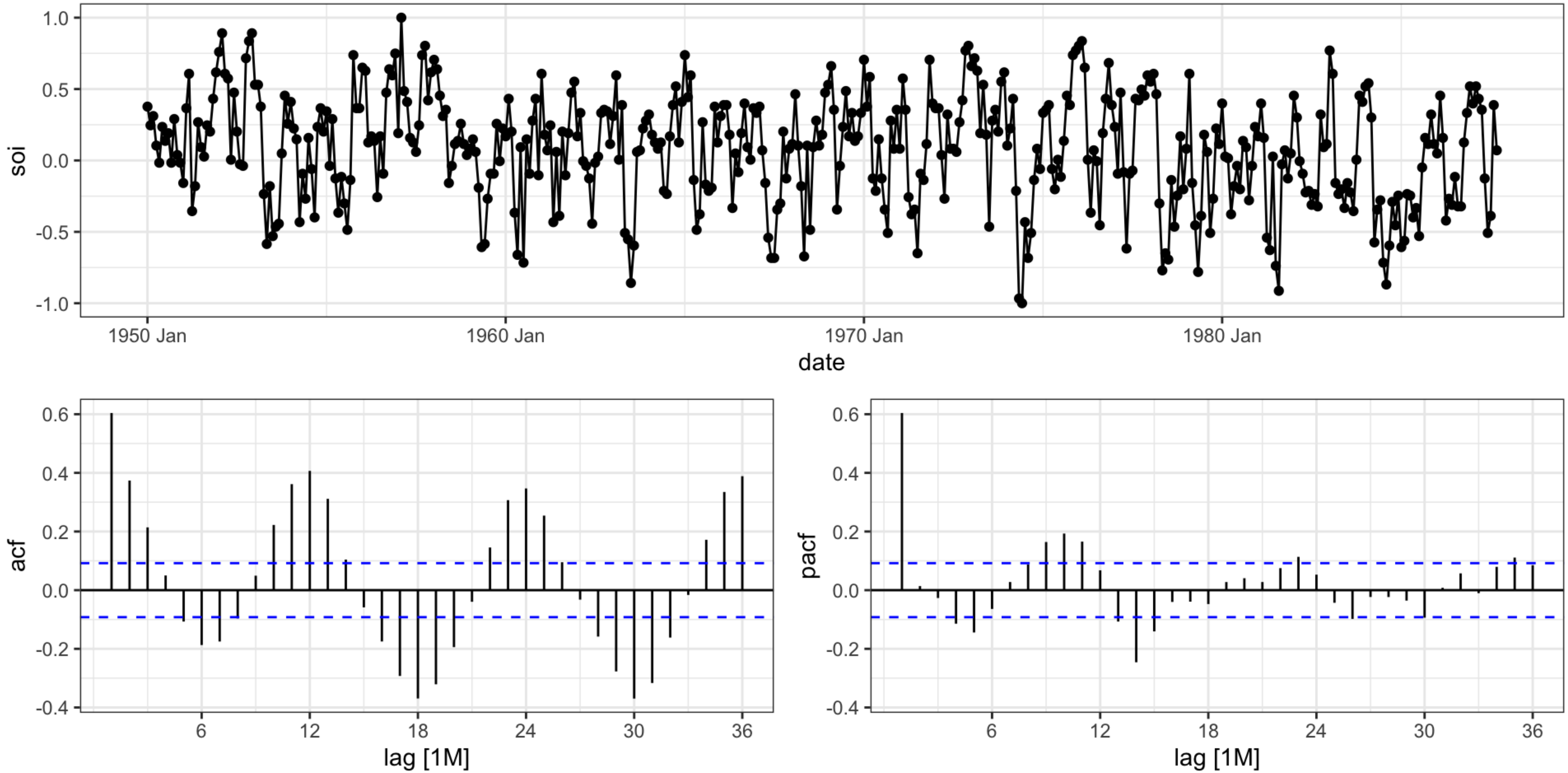
soi
recruitment
1.0
0.5
0.0
-0.5
-1.0
100
75
50
25
0
1950 Jan
1960 Jan
1970 Jan
1980 Jan
date [1M]

Relationship?



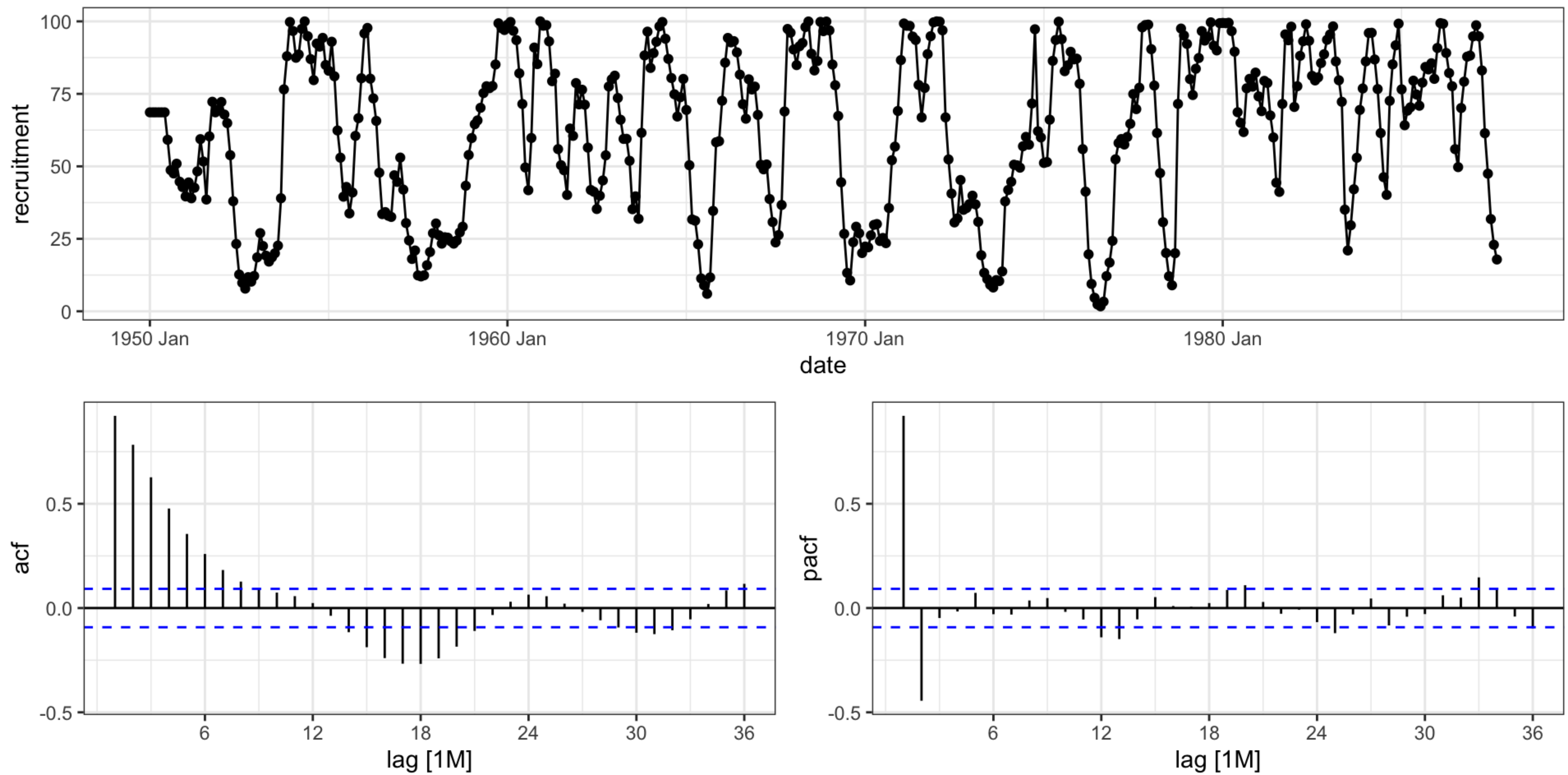
`soi` - ACF & PACF

```r
feasts::gg_tsdisplay(fish, y=soi, lag_max=36, plot_type = "partial")
```



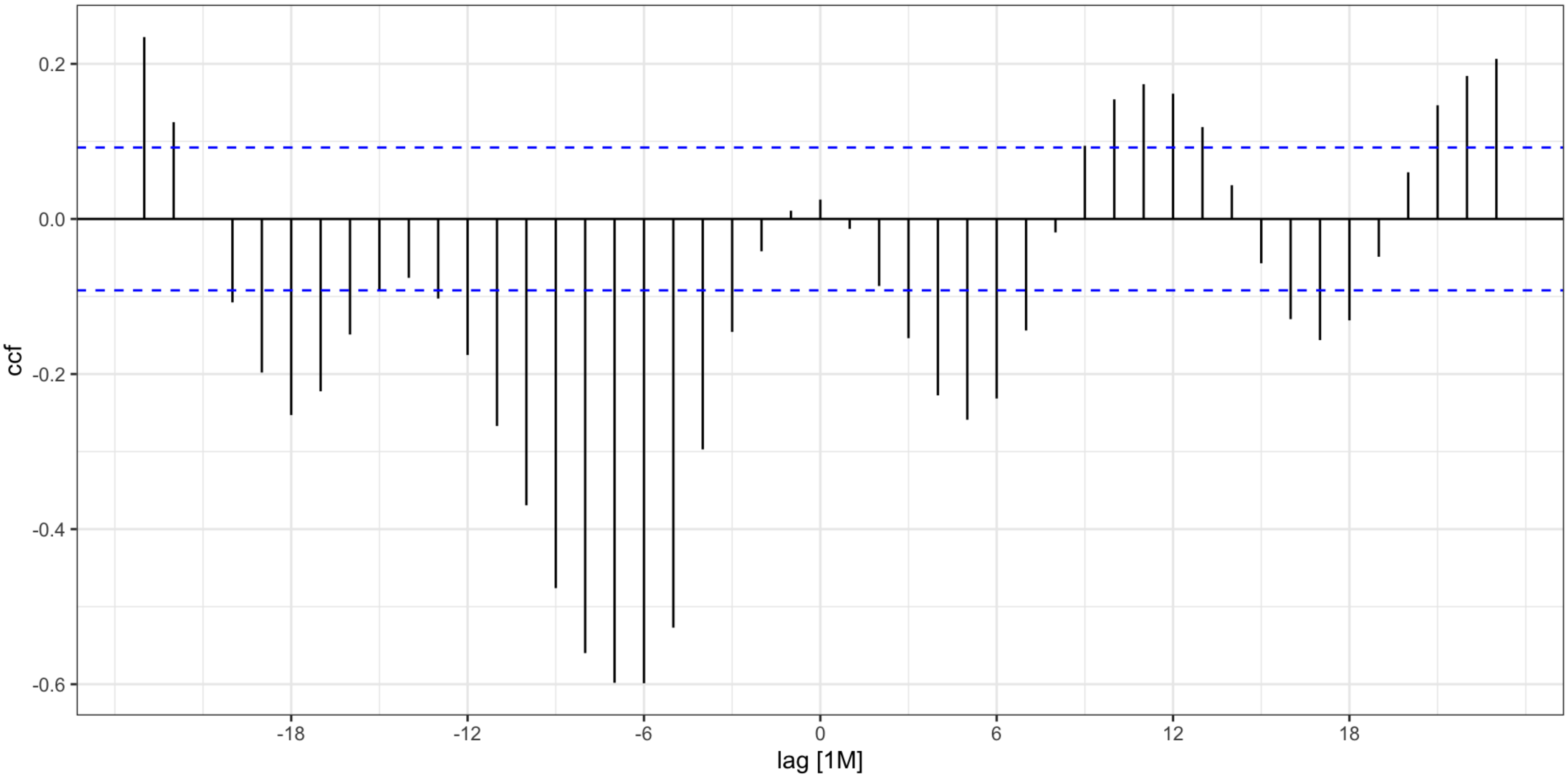
`recruitment` - ACF & PACF

```
feasts::gg_tsdisplay(fish, y=recruitment, lag_max=36, plot_type = "parti
```

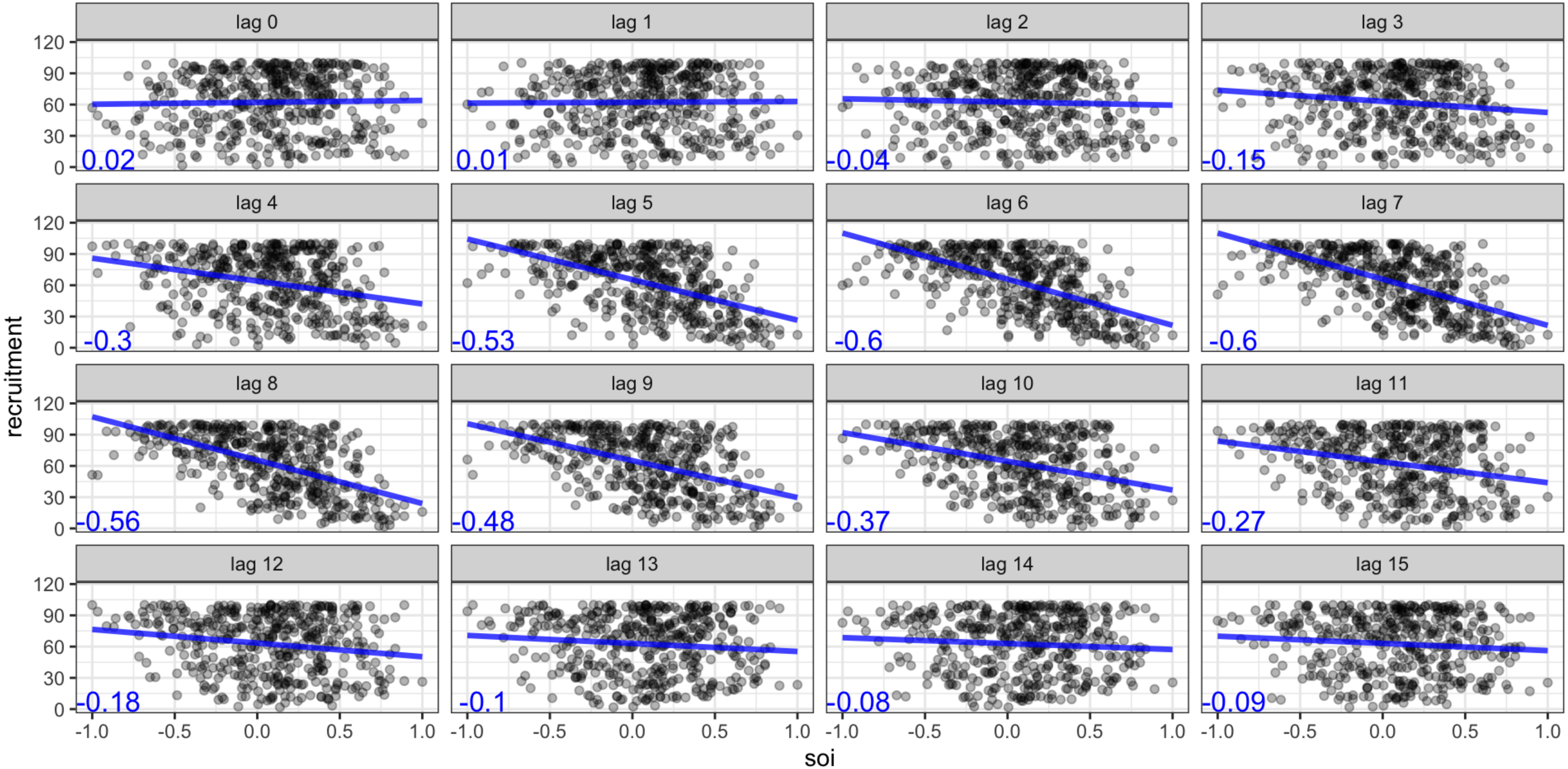


Cross correlation function

```r
feasts::CCF(fish, y = recruitment, x = soi) |>
  autoplot()
```



Cross correlation function - Scatter plots



The CCF gave us negative lags, why are we not considering them here?

Model

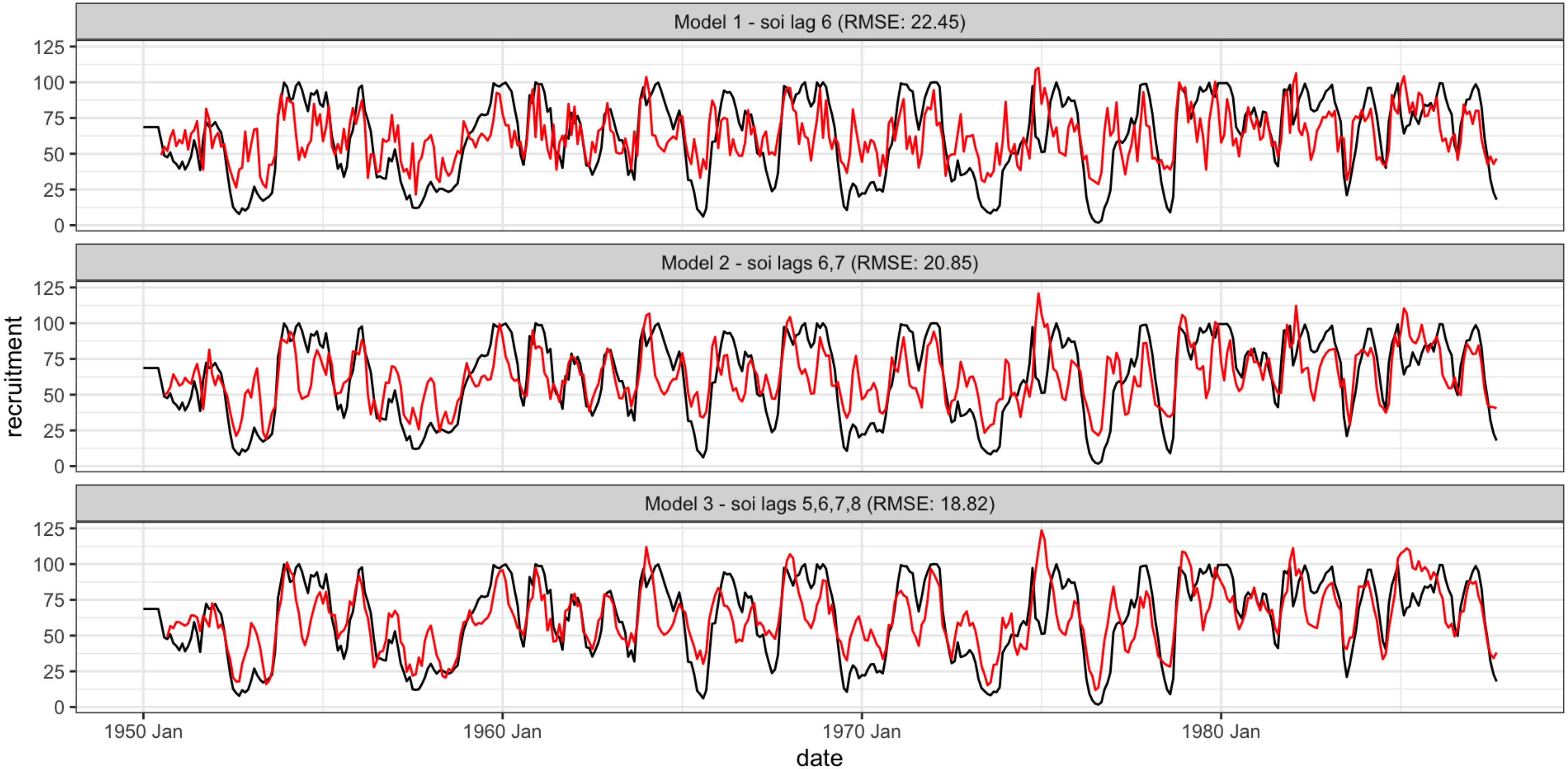
```r
model1 = lm(recruitment~lag(soi,6), data=fish)
model2 = lm(recruitment~lag(soi,6)+lag(soi,7), data=fish)
model3 = lm(recruitment~lag(soi,5)+lag(soi,6)+lag(soi,7)+lag(soi,8), data=fish)
```

```r
summary(model3)
```

```

Call:
lm(formula = recruitment ~ lag(soi, 5) + lag(soi, 6) + lag(soi, 
    7) + lag(soi, 8), data = fish)

Residuals:
    Min      1Q  Median      3Q     Max 
-72.409 -13.527   0.191  12.851  46.040 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)  67.9438     0.9306  73.007  < 2e-16 ***
lag(soi, 5) -19.1502     2.9508  -6.490 2.32e-10 ***
lag(soi, 6) -15.6894     3.4334  -4.570 6.36e-06 ***
lag(soi, 7) -13.4041     3.4332  -3.904 0.000109 ***
lag(soi, 8) -23.1480     2.9530  -7.839 3.46e-14 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Residual standard error: 18.93 on 440 degrees of freedom
  (8 observations deleted due to missingness)
```

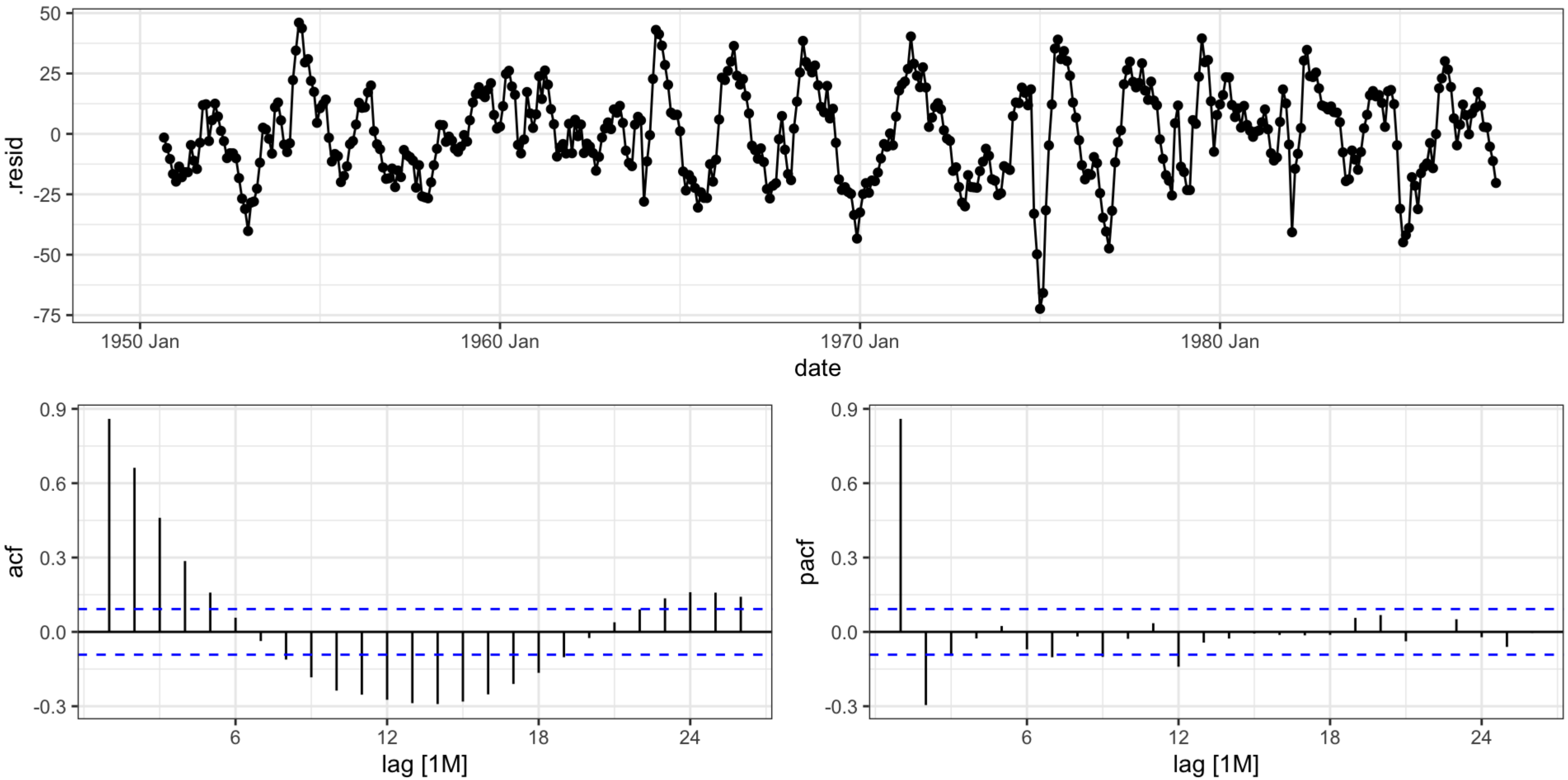
Prediction



Model 1 - soi lag 6 (RMSE: 22.45)
Model 2 - soi lags 6,7 (RMSE: 20.85)
Model 3 - soi lags 5,6,7,8 (RMSE: 18.82)
recruitment
125
100
75
50
25
0
1950 Jan
1960 Jan
1970 Jan
1980 Jan
date

Residual ACF - Model 3

```r
broom::augment(model3, newdata=fish) |>
  as_tsibble(index = date) |>
  feasts::gg_tsdisplay(y=.resid, plot_type = "partial")
```



Autoregessive model 4

```r
model4 = lm(
  recruitment~lag(recruitment,1) + lag(recruitment,2) +
              lag(soi,5)+lag(soi,6)+lag(soi,7)+lag(soi,8),
  data=fish
)
summary(model4)
```

```

Call:
lm(formula = recruitment ~ lag(recruitment, 1) + lag(recruitment, 
    2) + lag(soi, 5) + lag(soi, 6) + lag(soi, 7) + lag(soi, 8), 
    data = fish)

Residuals:
    Min      1Q  Median      3Q     Max 
-51.996  -2.892   0.103   3.117  28.579 

Coefficients:
                     Estimate Std. Error t value Pr(>|t|)    
(Intercept)          10.25007    1.17081   8.755  < 2e-16 ***
lag(recruitment, 1)   1.25301    0.04312  29.061  < 2e-16 ***
lag(recruitment, 2)  -0.39961    0.03998  -9.995  < 2e-16 ***
lag(soi, 5)         -20.76309    1.09906 -18.892  < 2e-16 ***
lag(soi, 6)           9.71918    1.56265   6.220 1.16e-09 ***
lag(soi, 7)          -1.01131    1.31912  -0.767   0.4437    
```

```
lag(soi, 8)          -2.29814    1.20730  -1.904   0.0576 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

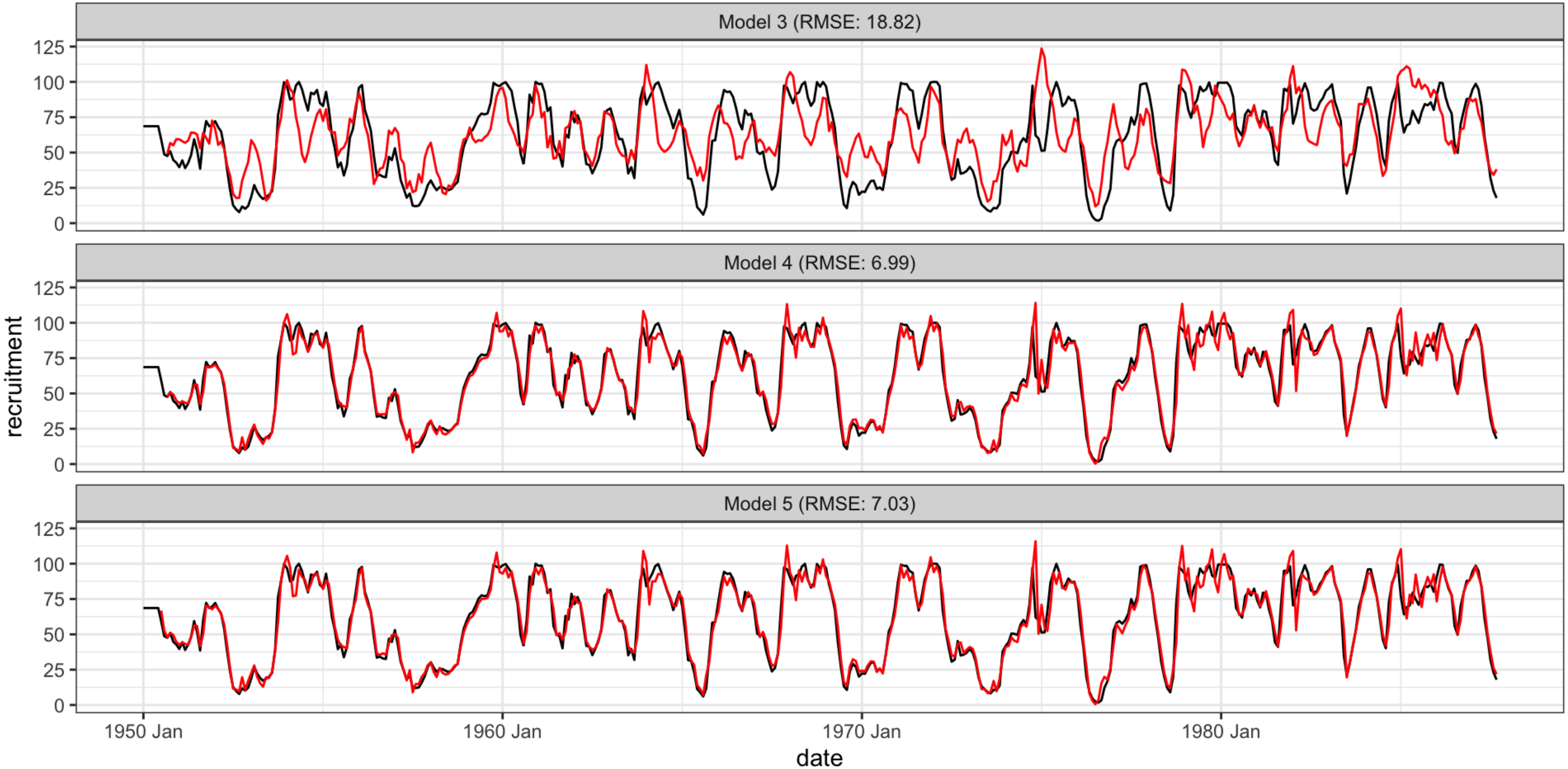
Autoregessive model 5

```r
model5 = lm(
  recruitment~lag(recruitment,1) + lag(recruitment,2) +
              lag(soi,5) + lag(soi,6),
  data=fish
)
summary(model5)
```

```

Call:
lm(formula = recruitment ~ lag(recruitment, 1) + lag(recruitment, 
    2) + lag(soi, 5) + lag(soi, 6), data = fish)

Residuals:
    Min      1Q  Median      3Q     Max 
-53.786  -2.999  -0.035   3.031  27.669 

Coefficients:
                     Estimate Std. Error t value Pr(>|t|)    
(Intercept)           8.78498    1.00171   8.770  < 2e-16 ***
lag(recruitment, 1)   1.24575    0.04314  28.879  < 2e-16 ***
lag(recruitment, 2)  -0.37193    0.03846  -9.670  < 2e-16 ***
lag(soi, 5)         -20.83776    1.10208 -18.908  < 2e-16 ***
lag(soi, 6)           8.55600    1.43146   5.977 4.68e-09 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Residual standard error: 7.069 on 442 degrees of freedom
  (6 observations deleted due to missingness)
```

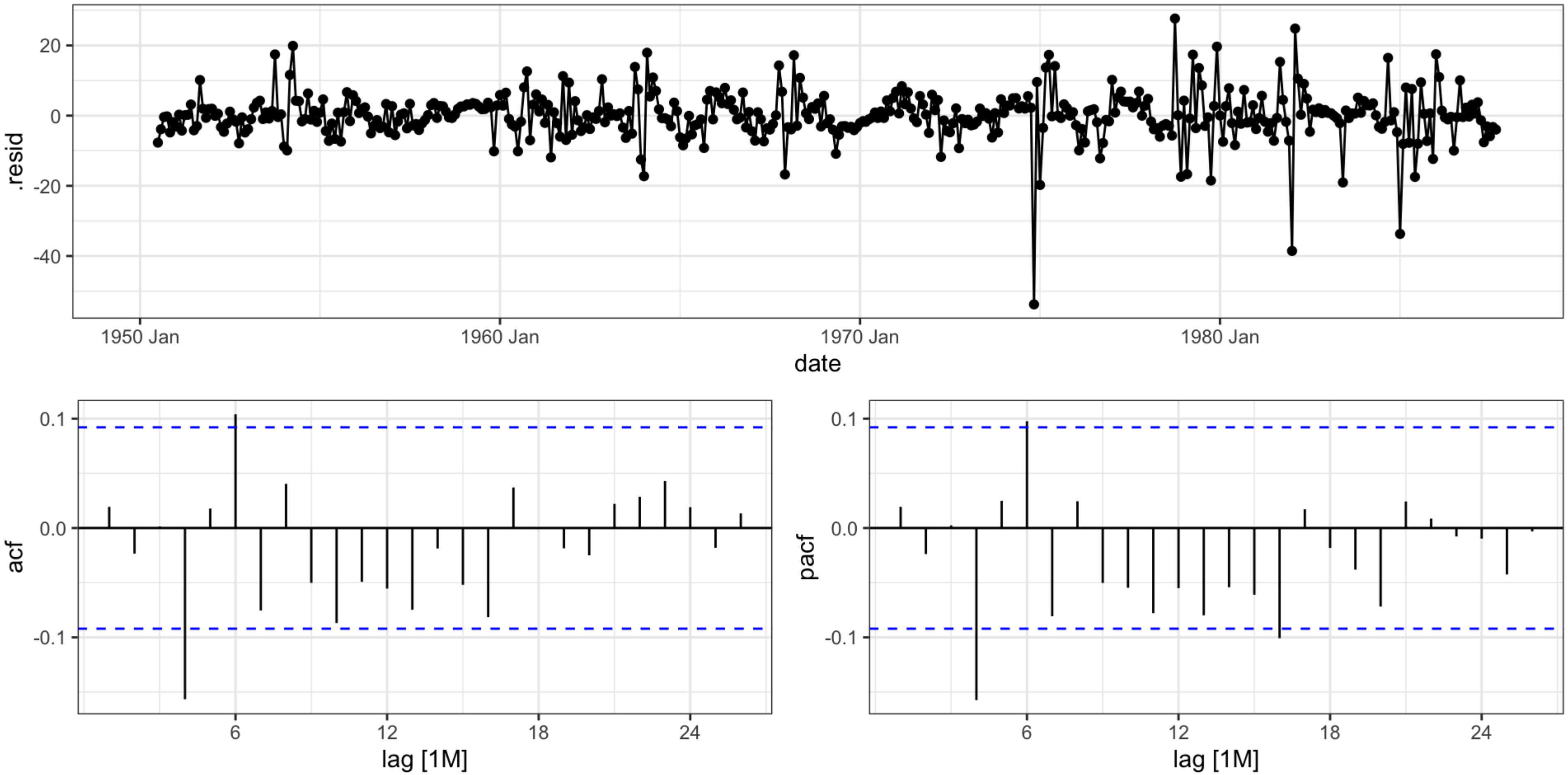
Prediction



Model 3 (RMSE: 18.82)
Model 4 (RMSE: 6.99)
Model 5 (RMSE: 7.03)
recruitment
125
100
75
50
25
0
1950 Jan
1960 Jan
1970 Jan
1980 Jan
date

Residual ACF - Model 5

```r
broom::augment(model5, newdata=fish) |>
  as_tsibble(index = date) |>
  feasts::gg_tsdisplay(y=.resid, plot_type = "partial")
```



Non-stationarity

Non-stationary models

> All happy families are alike; each unhappy family is unhappy in its own way.
>
> - Tolstoy, Anna Karenina

This applies to time series models as well, just replace happy family with stationary model.

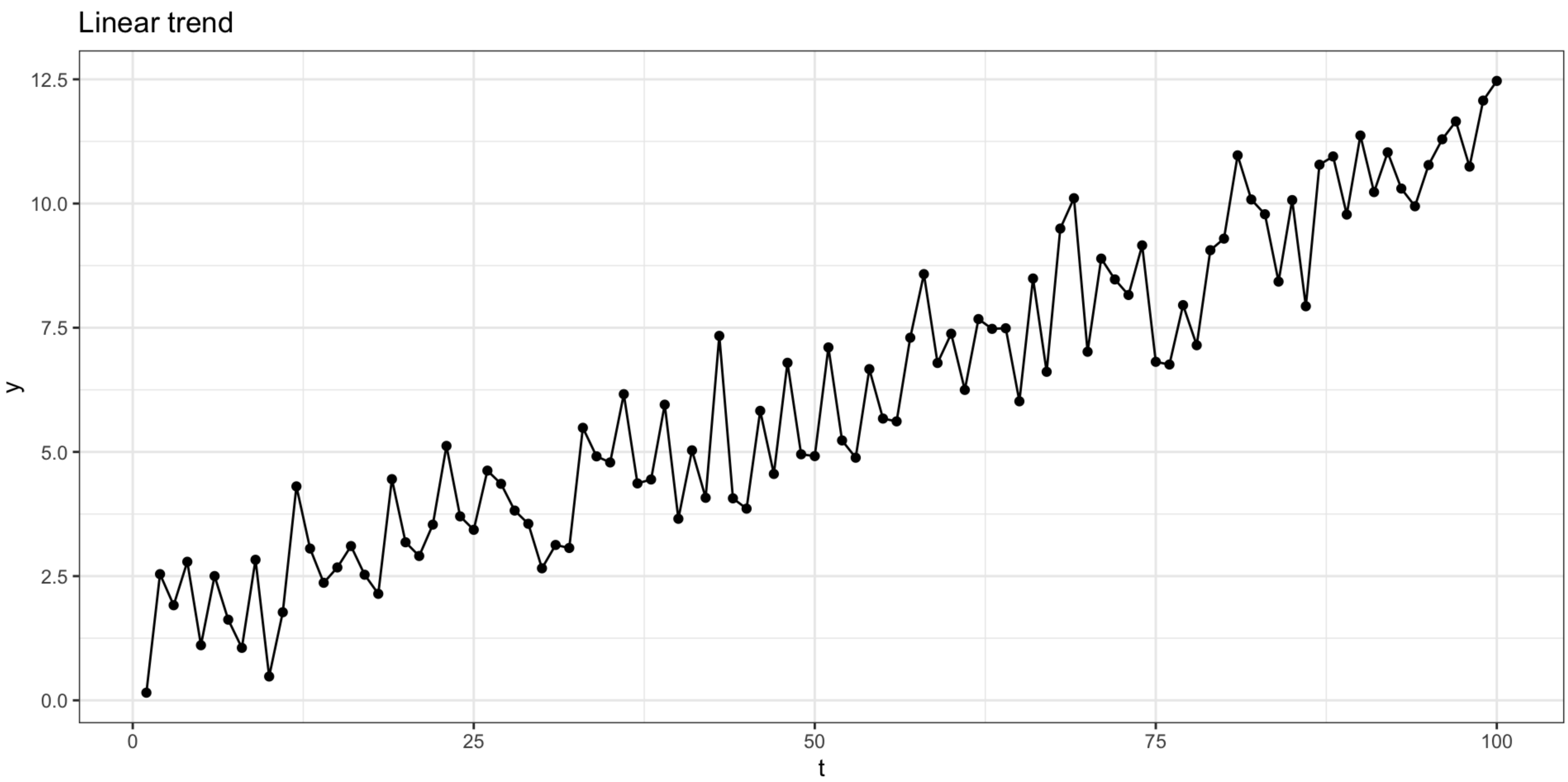
A simple example of a non-stationary time series is a trend stationary model

$$y_t = \mu(t) + w_t$$

where $\mu(t)$ denotes a time dependent trend and w_t is a white noise (stationary) process.

Linear trend model

Lets imagine a simple model where $y_t = \delta + \beta t + x_t$ where δ and β are constants and x_t is a stationary process.

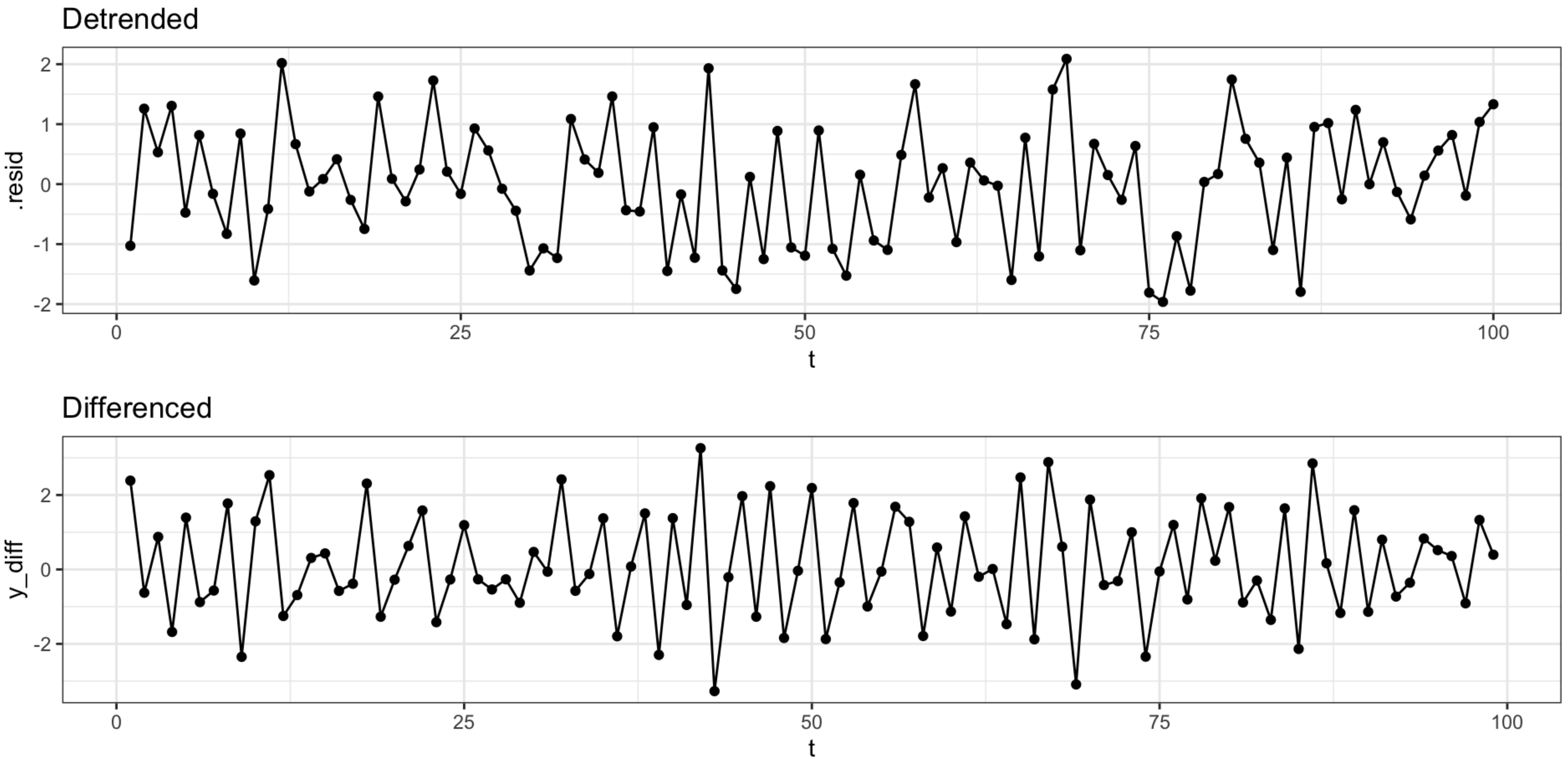


Differencing

An simple approach to remove trend is to difference your response variable, specifically examine $d_t = y_t - y_{t-1}$ instead of y_t.

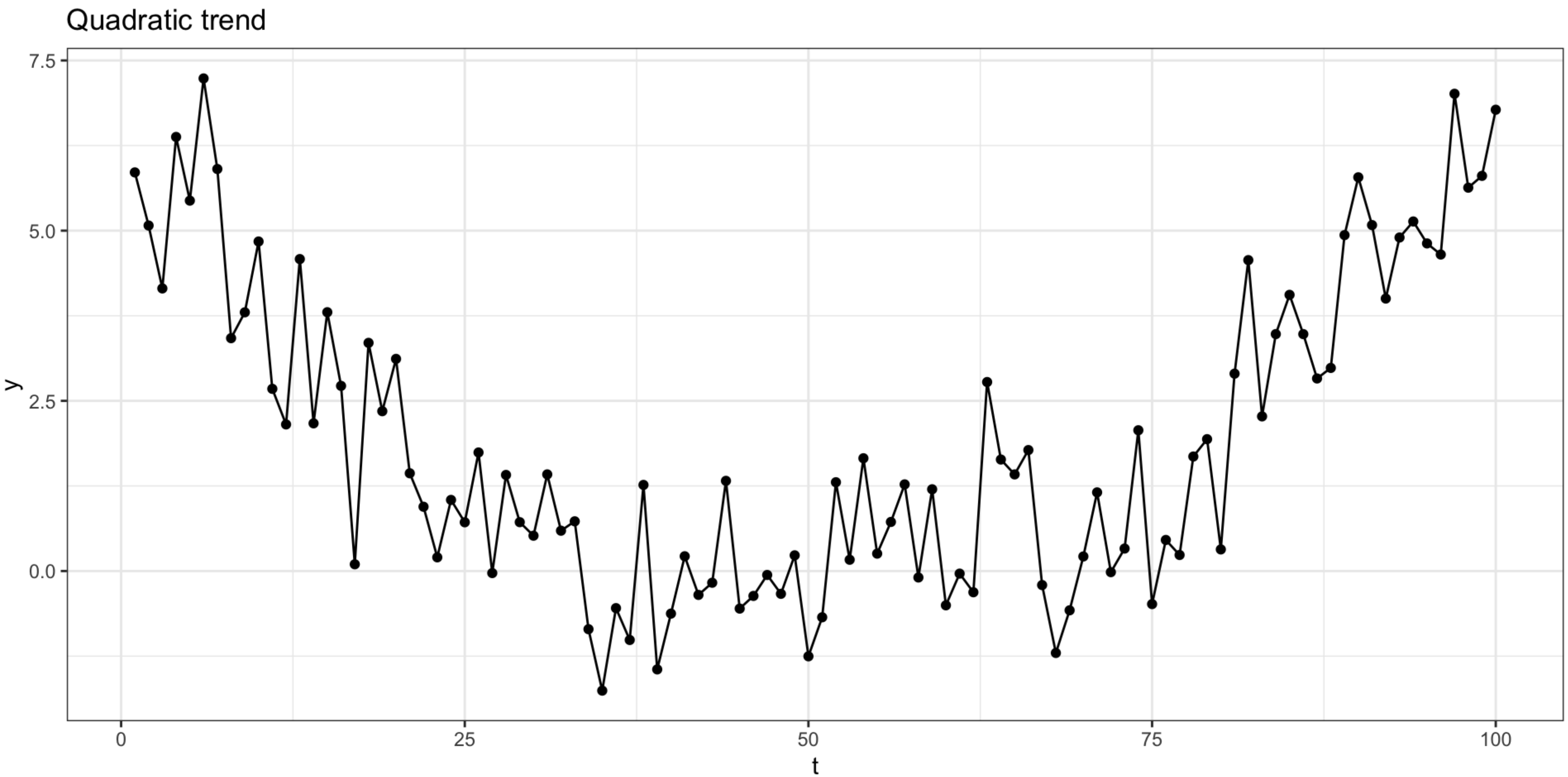
Is the linear trend model stationary after differencing?

Detrending vs Differencing

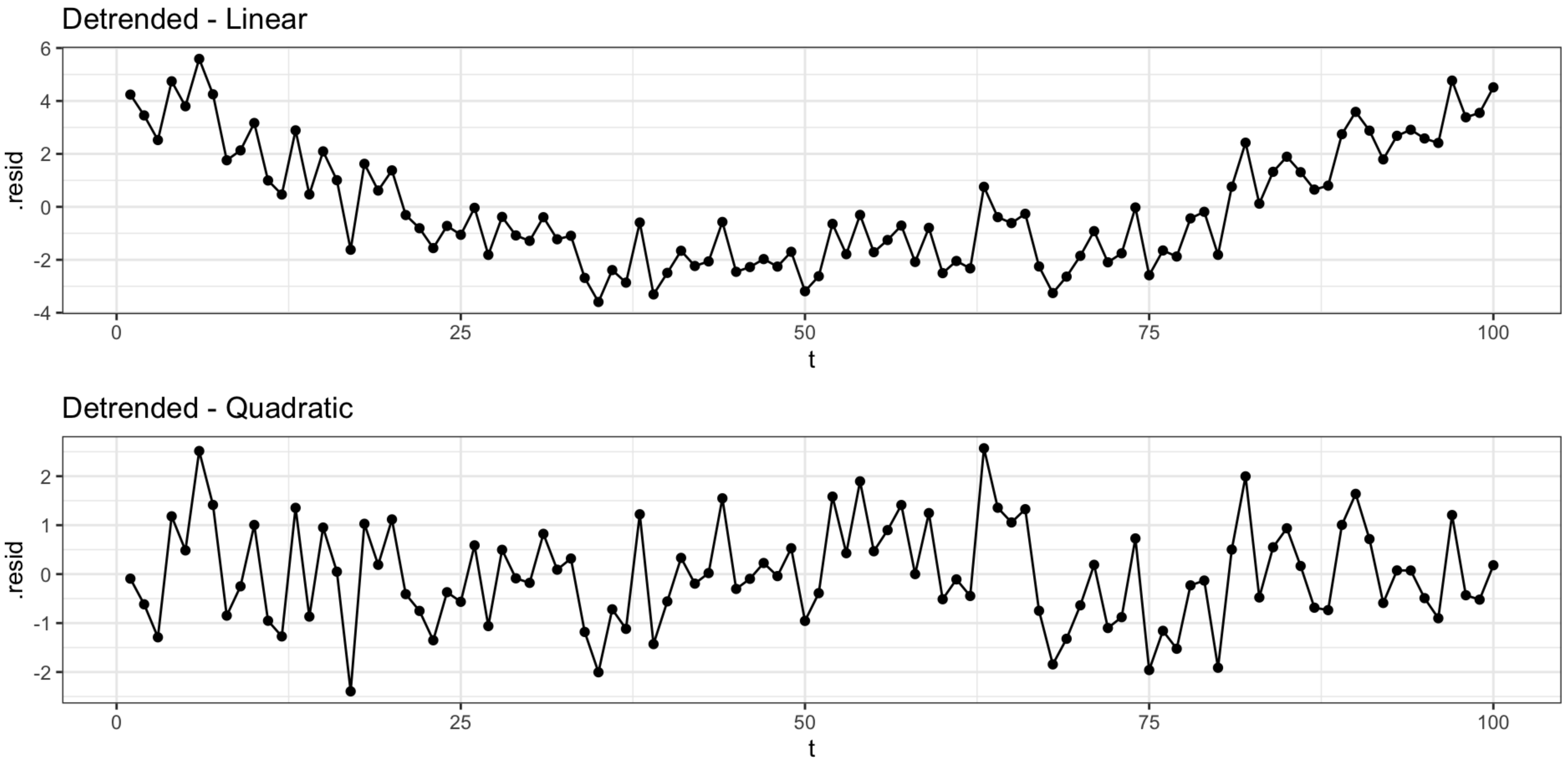


Quadratic trend model

Lets imagine another simple model where $y_t = \delta + \beta t + \gamma t^2 + x_t$ where δ, β, and γ are constants and x_t is a stationary process.



Detrending



Detrended - Linear
6
4
2
0
-2
-4
.resid
0
25
50
75
100
t
Detrended - Quadratic
2
1
0
-1
-2
.resid
0
25
50
75
100
t

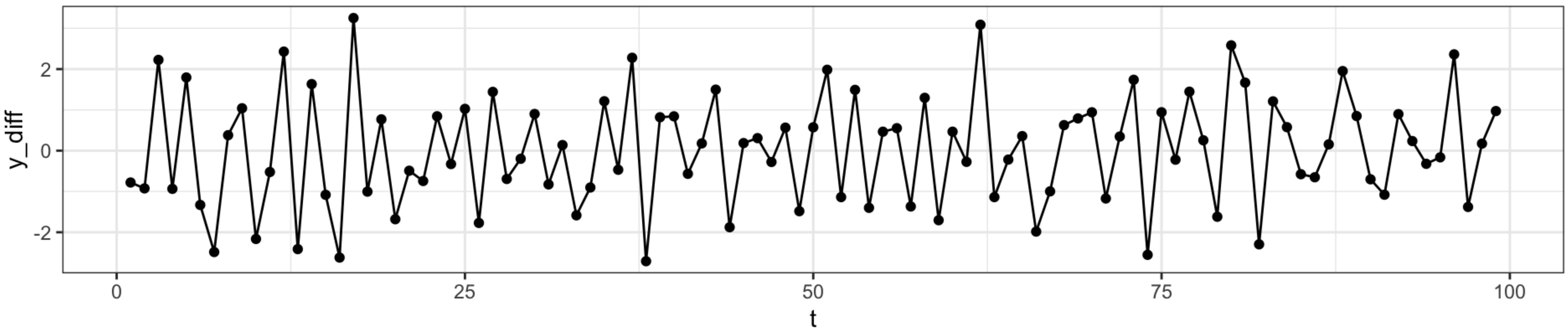
2nd order differencing

Let $d_t = y_t - y_{t-1}$ be a first order difference then $d_t - d_{t-1}$ is a 2nd order difference.

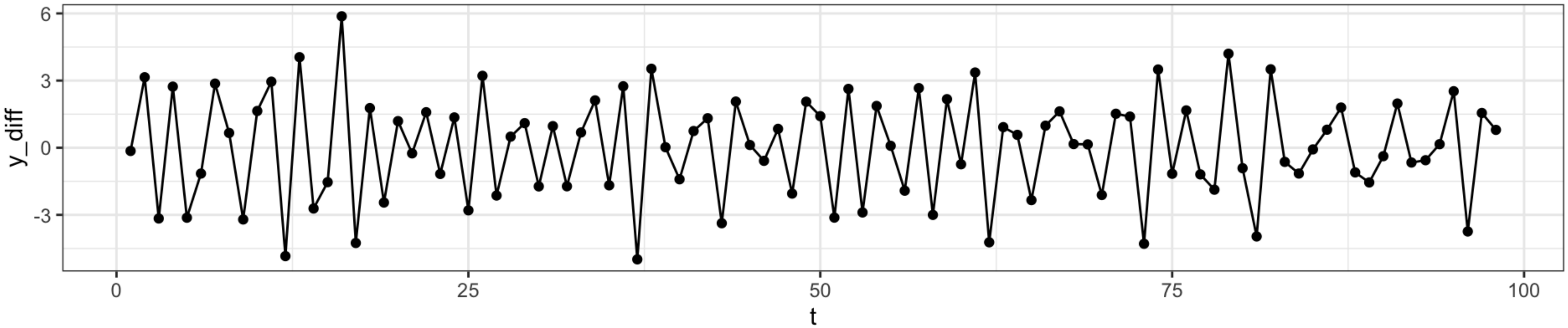
Is the quadratic trend model stationary after 2nd order differencing?

Differencing

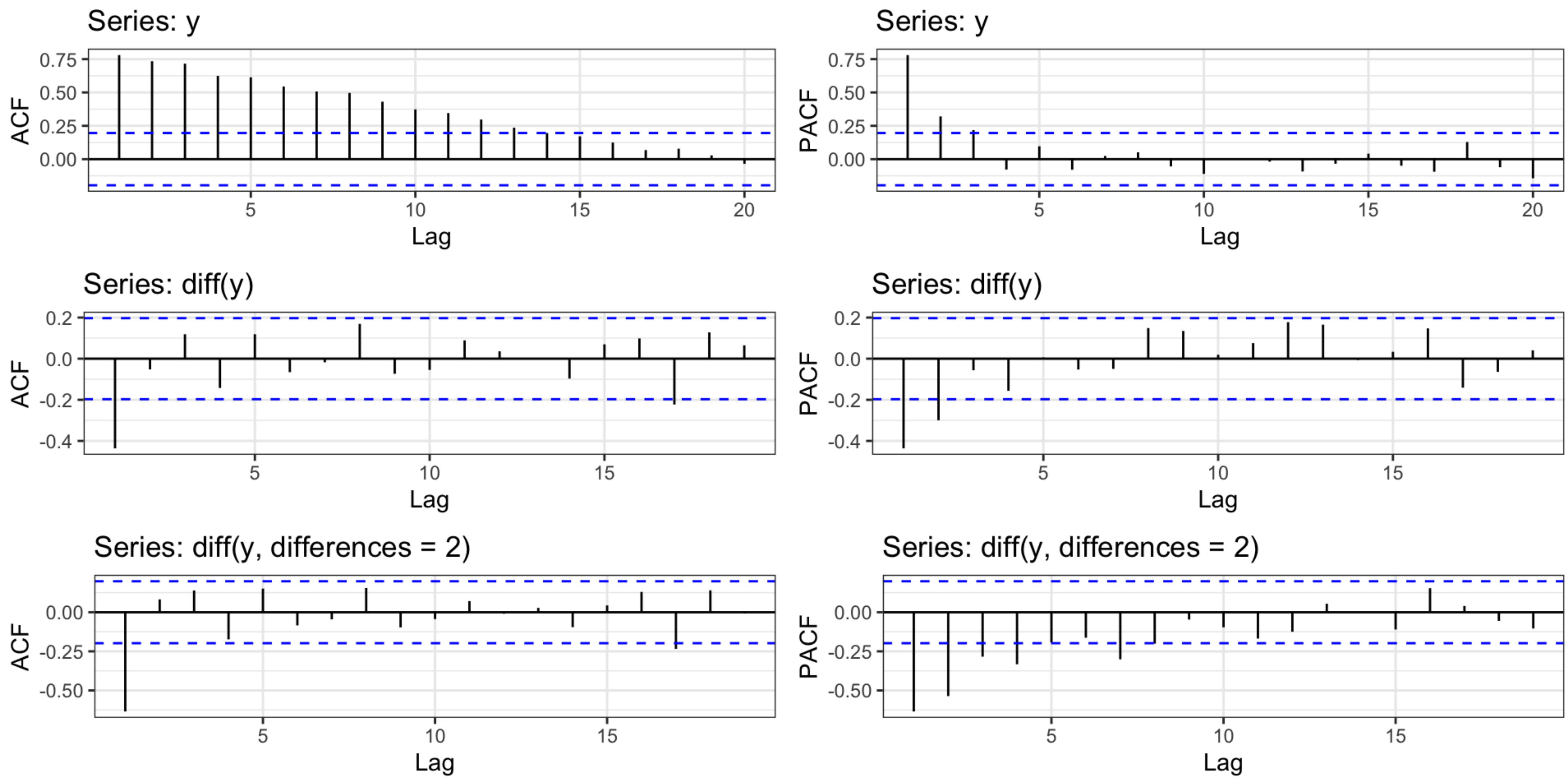
1st Difference



2nd Difference



Differencing - ACF



AR Models

AR(1)

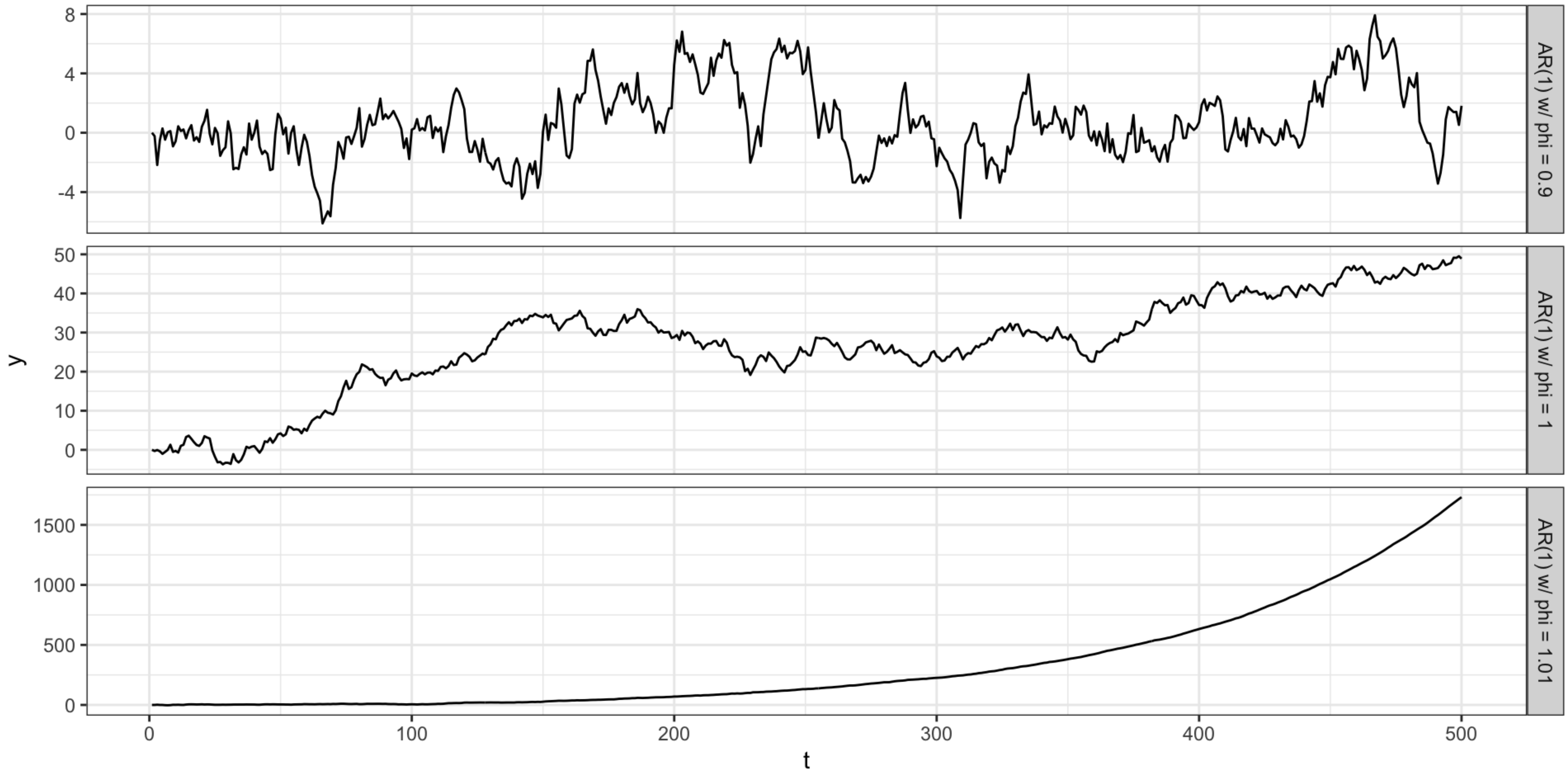
Last time we mentioned a random walk with trend process where $y_t = \delta + y_{t-1} + w_t$.

The AR(1) process is a generalization of this where we include a coefficient in front of the y_{t-1} term.

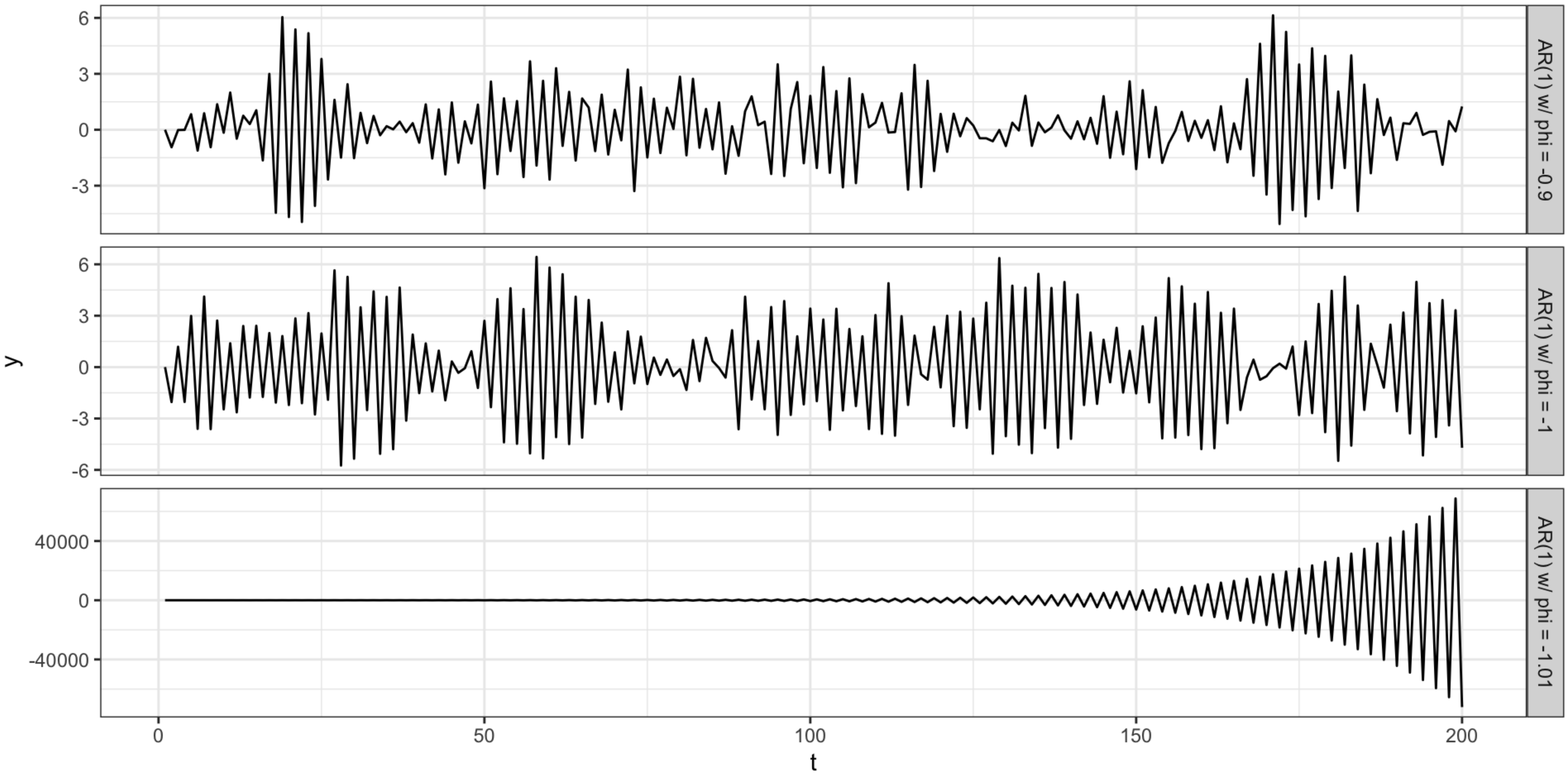
$$\text{AR}(1): \quad y_t = \delta + \phi\, y_{t-1} + w_t$$

$$w_t \sim N(0, \sigma_w^2)$$

AR(1) - Positive ϕ



AR(1) - Negative ϕ



Stationarity of $\text{AR}(1)$ processes

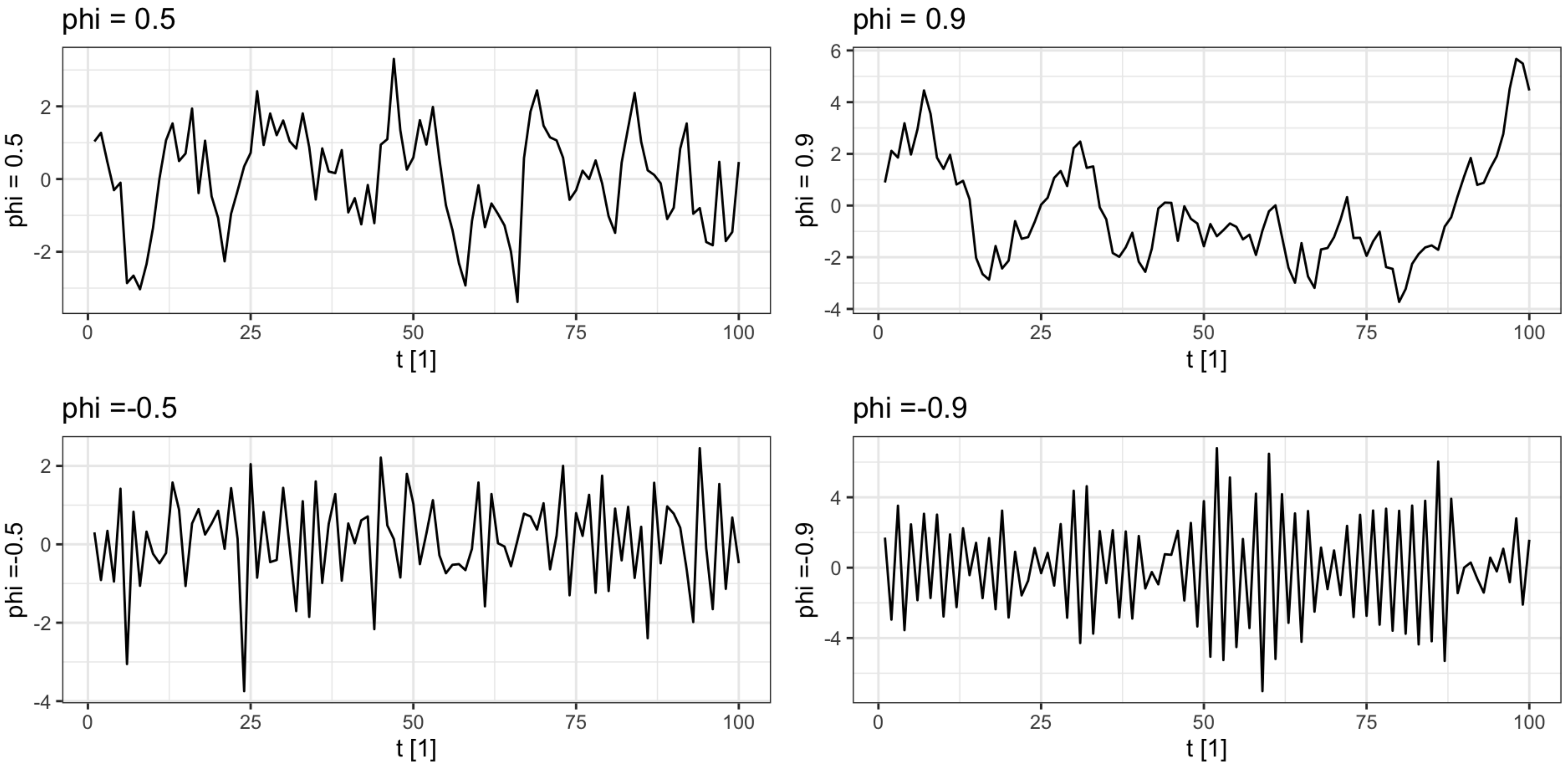
Lets rewrite the AR(1) without any autoregressive terms

Stationarity of $\text{AR}(1)$ processes

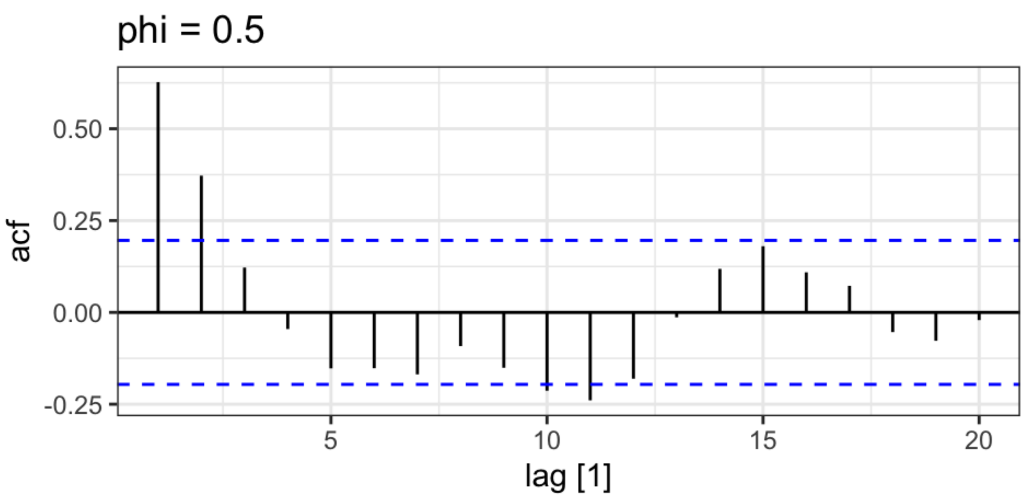
Under what conditions will an AR(1) process be stationary?

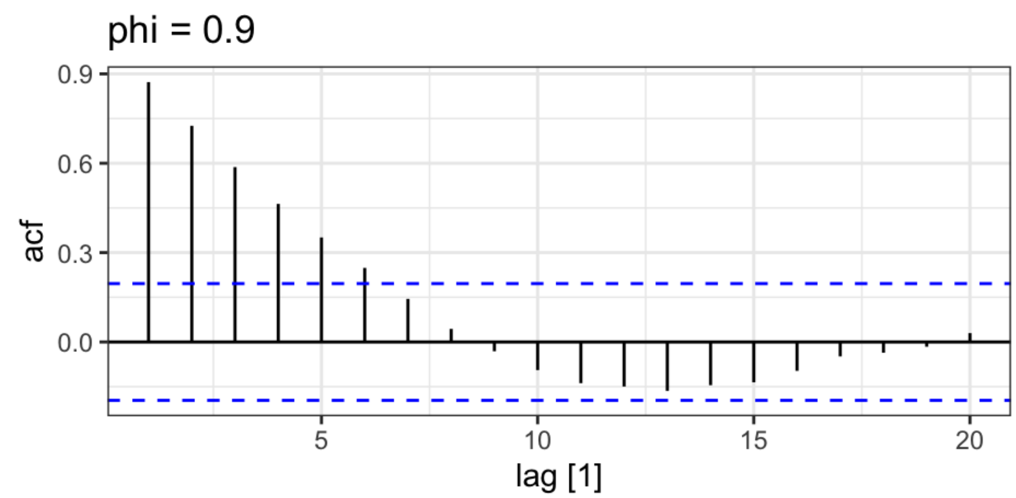
Properties of a stationary $\text{AR}(1)$ process

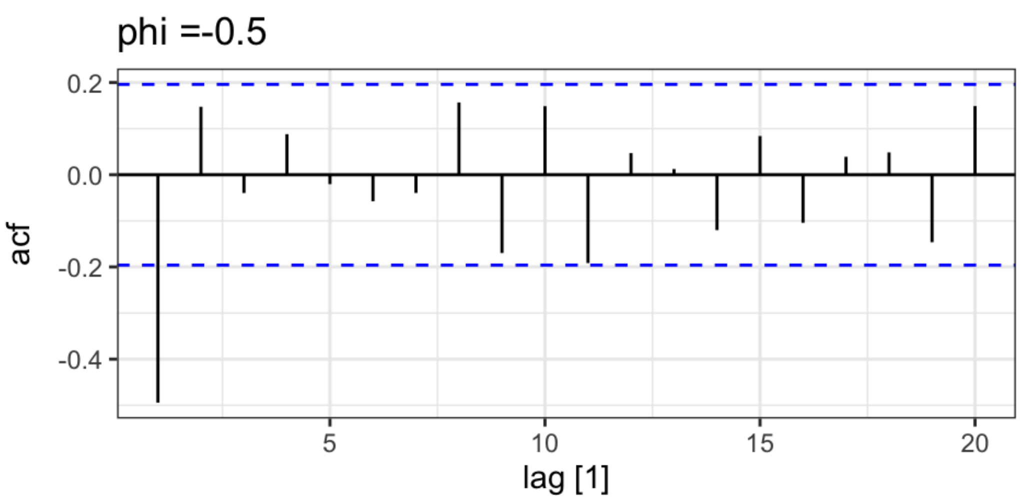
Identifying AR(1) Processes

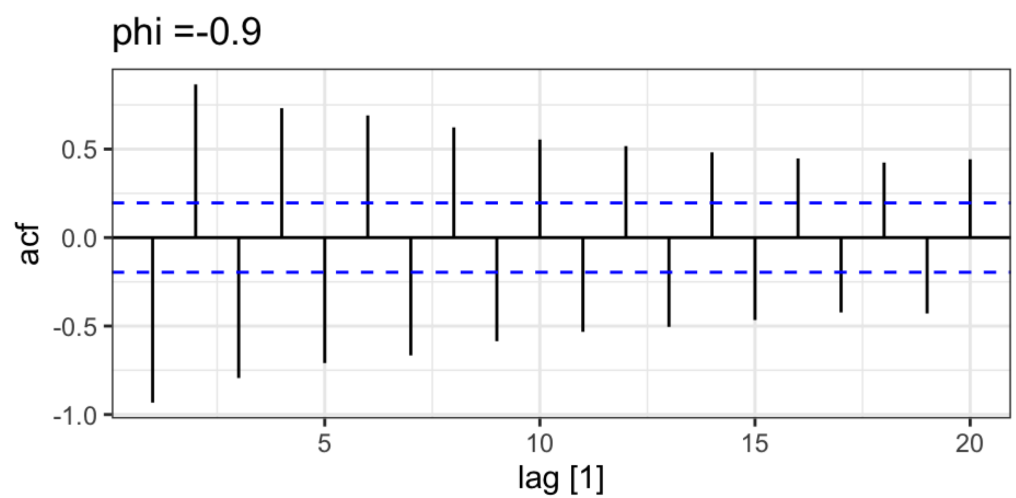


Identifying AR(1) Processes - ACFs









Identifying AR(1) Processes - PACFs