



## Time Series Analysis in Earth Engine

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<https://goo.gl/lMwd2Y>

**Disclaimer:** this is not a statistics course!

(It's about how to do things in Earth Engine)

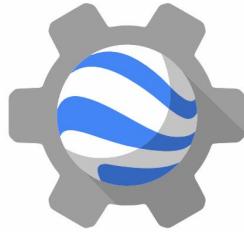
See [this text](#) for background:



Robert H. Shumway  
David S. Stoffer

# Time Series Analysis and Applications

EZ Edition  
with R Examples



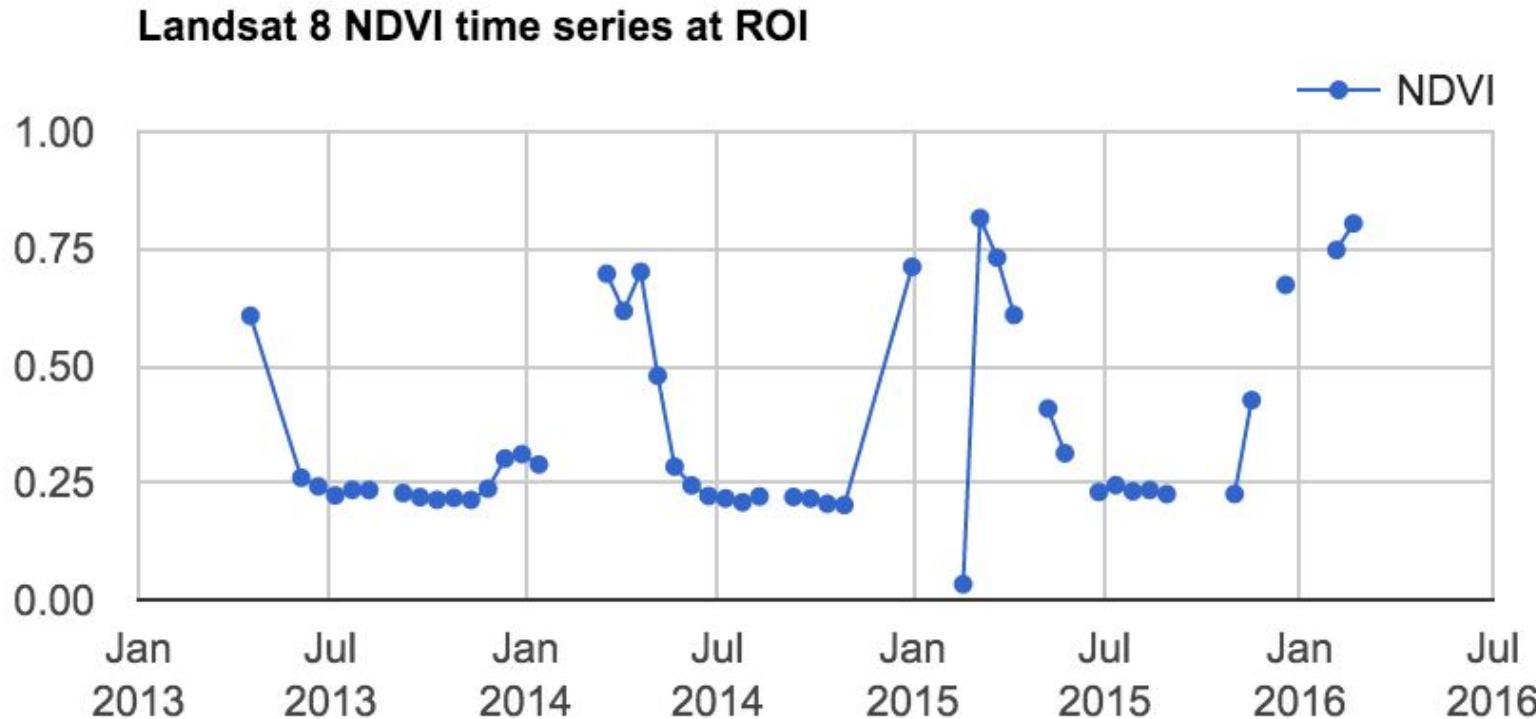
# What this course IS about:

- Our time series: Landsat 8 NDVI, about 64 images (and growing...)
- A framework for time series analysis in Earth Engine using **join()**, **map()**, **reduce()**
- Earth Engine examples:
  - Linear modeling
  - Harmonic modeling
  - Auto-covariance and auto-correlation
  - Cross-covariance and cross-correlation
  - Auto-regressive models (time permitting)

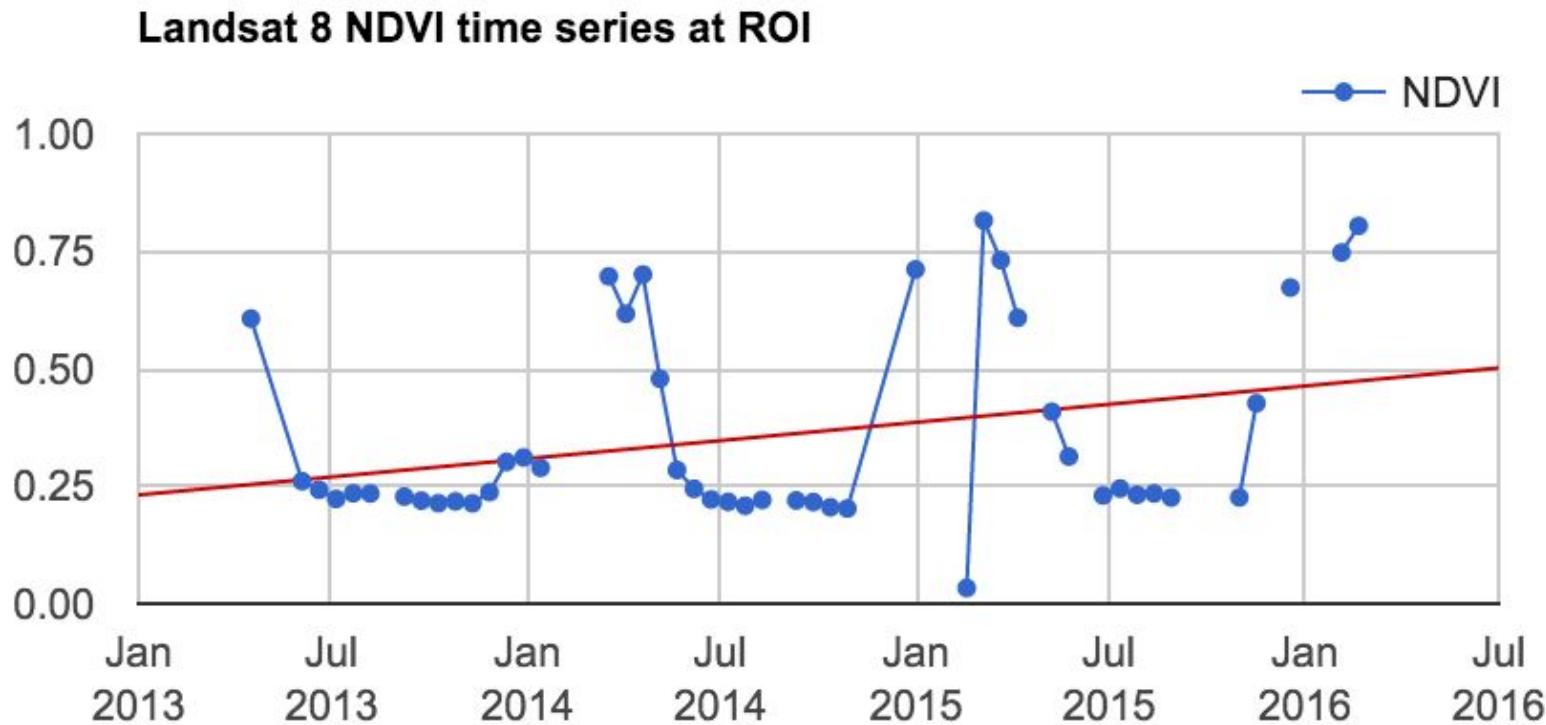


# Linear model of time

## ImageCollection: irregularly spaced points, missing data, noisy data



Red line: linear trend



## Linear model of time (trend):

$$p_t = \beta_0 + \beta_1 t + e_t$$

$p_t$  = NDVI at time  $t$

$t$  = time

$e_t$  = random error

We want  $\beta$ 's for every pixel...

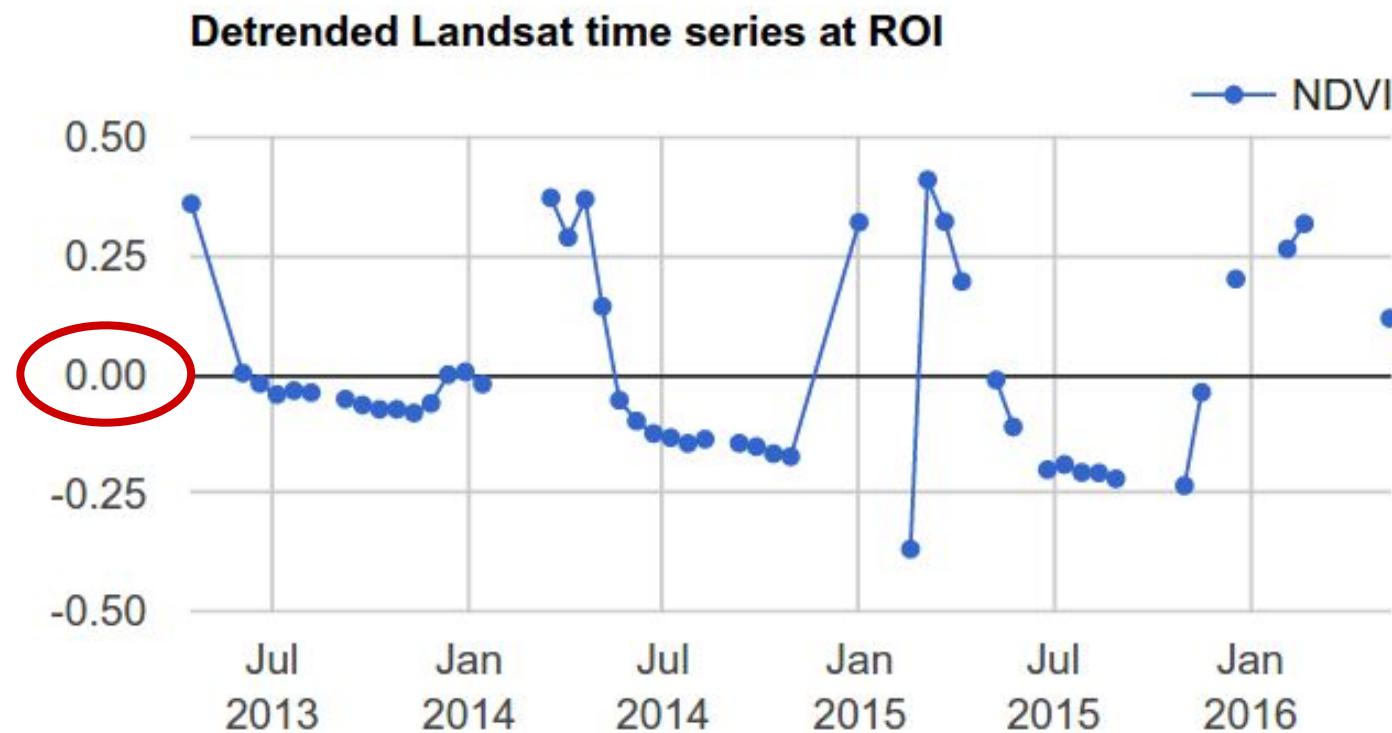
To give each image bands representing independent variables, map( ) a function over the collection:

```
var addVariables = function(image) {  
  var date = ee.Date(image.get(timeField));  
  var years = date.difference(ee.Date('1970-01-01'), 'year');  
  return image  
    .addBands(image.normalizedDifference(['B5', 'B4']).rename('NDVI')).float()  
    .addBands(ee.Image(years).rename('t').float())  
    .addBands(ee.Image.constant(1));  
};
```

# Compute the $\beta$ 's using the `linearRegression` reducer:

```
var independents = ee.List(['constant', 't']);  
  
var dependent = ee.String('NDVI');  
  
var trend = filteredLandsat.select(independents.add(dependent))  
    .reduce(ee.Reducer.linearRegression(independents.length(), 1));  
  
var coefficients = trend.select('coefficients')  
    .arrayProject([0])  
    .arrayFlatten([independents]);
```

"Detrend" (compute  $p_t - \hat{p}_t$ ):



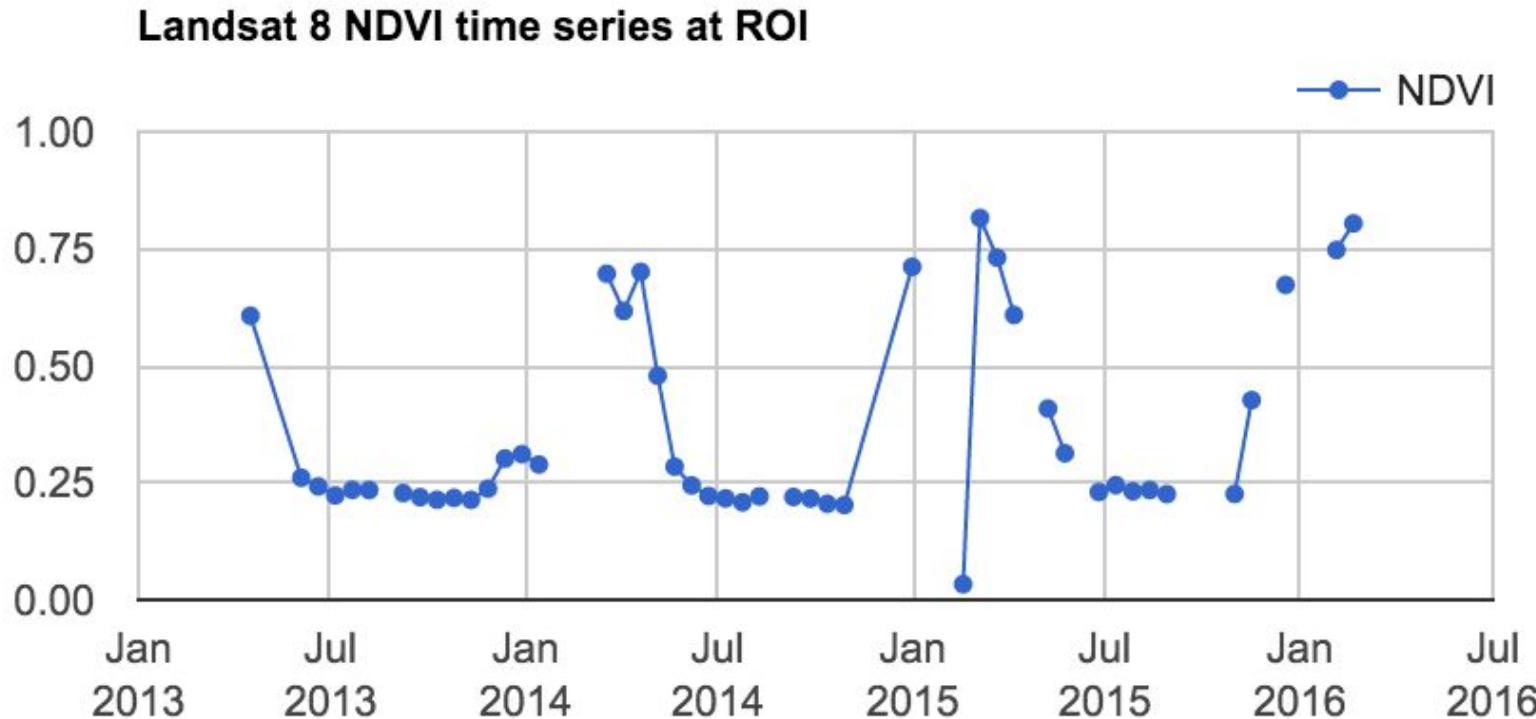
To detrend, map() a function over the collection:

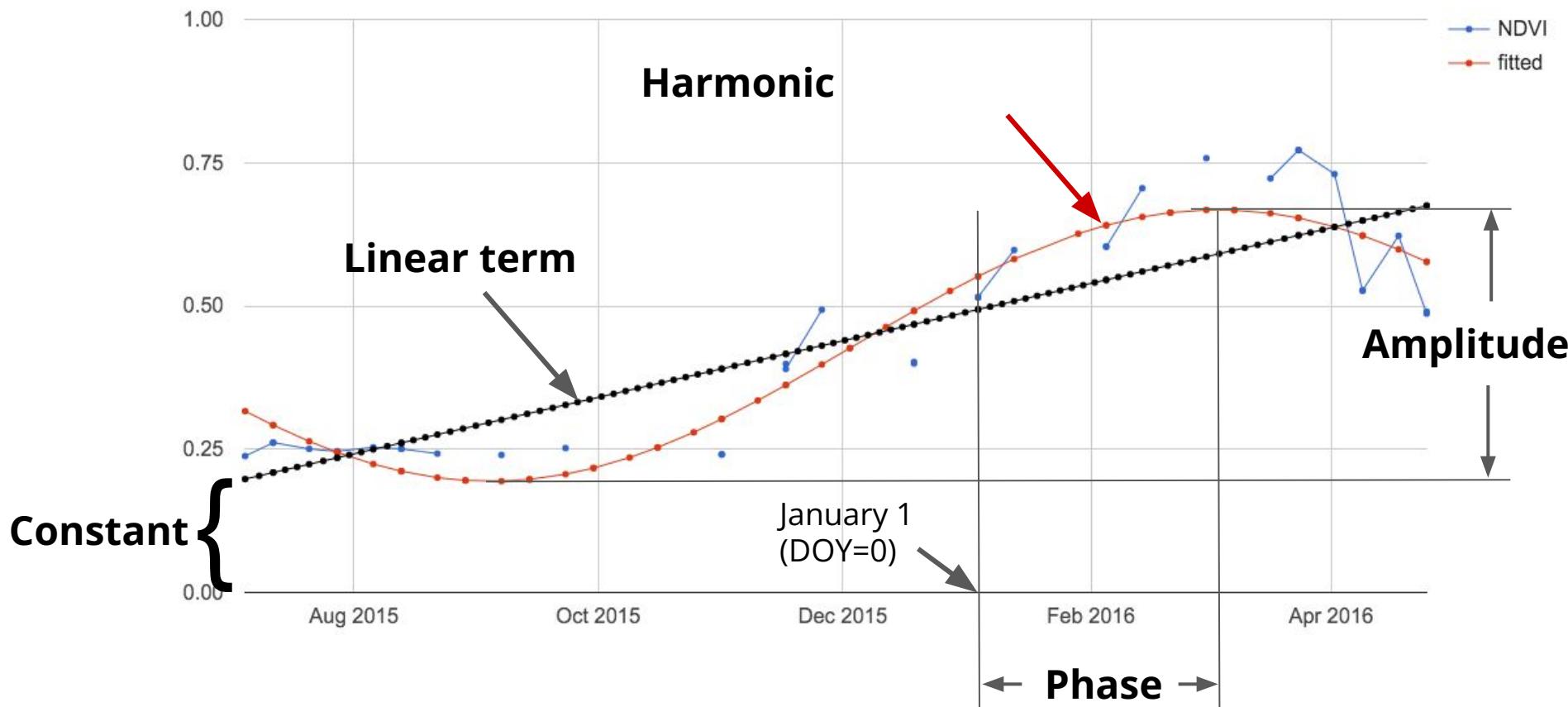
```
var detrended = filteredLandsat.map(function(image) {  
  return image.select(dependent).subtract(  
    image.select(independents).multiply(coefficients).reduce('sum'))  
    .rename(dependent)  
    .copyProperties(image, [timeField]);  
});
```

# Harmonic model of time



# Original data: a time series with a regular cycle?





Shumway and Stoffer (2017), equations 4.1-4.2:

$$A\cos(2\pi\omega t - \varphi) = \beta_2 \cos(2\pi\omega t) + \beta_3 \sin(2\pi\omega t)$$

$$\beta_2 = A\cos(\varphi)$$

$$\beta_3 = A\sin(\varphi)$$

$$A = \text{amplitude} = (\beta_2^2 + \beta_3^2)^{1/2}$$

$$\varphi = \text{phase} = \tan(\beta_3/\beta_2)$$

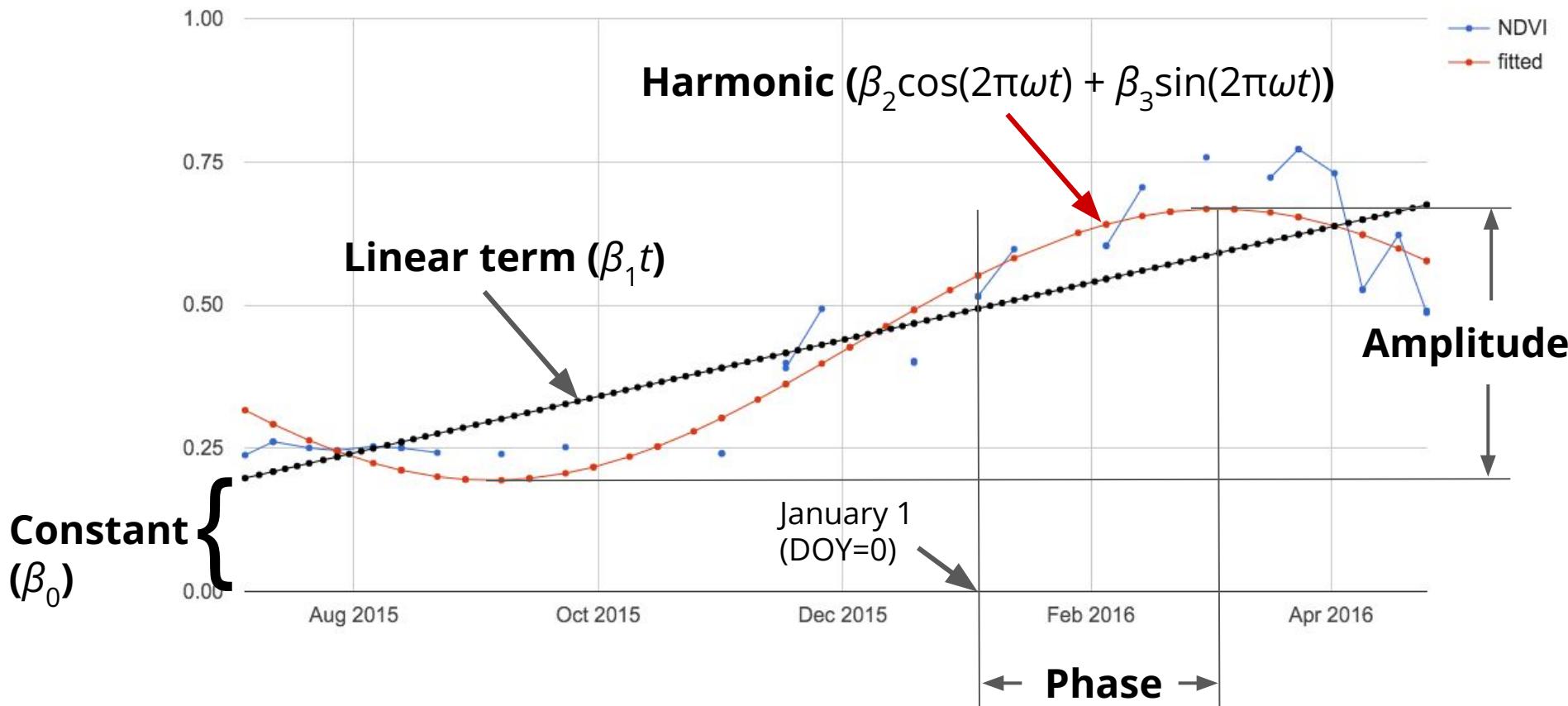
$\omega$  = angular frequency

Use this to linearize the harmonic function of phase and amplitude...

Fit the following linear model with ( $\omega = 1$ ):

$$\begin{aligned} p_t &= NDVI_t = \beta_0 + \beta_1 t + A \cos(2\pi\omega t - \varphi) + e_t \\ &= \beta_0 + \beta_1 t + \beta_2 \cos(2\pi\omega t) + \beta_3 \sin(2\pi\omega t) + e_t \end{aligned}$$

$$\text{NDVI}_t = \beta_0 + \beta_1 t + \beta_2 \cos(2\pi\omega t) + \beta_3 \sin(2\pi\omega t) + \dots$$



# Compute the $\beta$ 's using the `linearRegression` reducer:

```
var harmonicIndependents = ee.List(['constant', 't', 'cos', 'sin']);

var harmonicLandsat = filteredLandsat.map(function(image) {
  var timeRadians = image.select('t').multiply(2 * Math.PI);
  return image
    .addBands(timeRadians.cos().rename('cos'))
    .addBands(timeRadians.sin().rename('sin')));
});

var harmonicTrend = harmonicLandsat
  .select(harmonicIndependents.add(dependent))
  .reduce(ee.Reducer.linearRegression(harmonicIndependents.length(), 1));
```

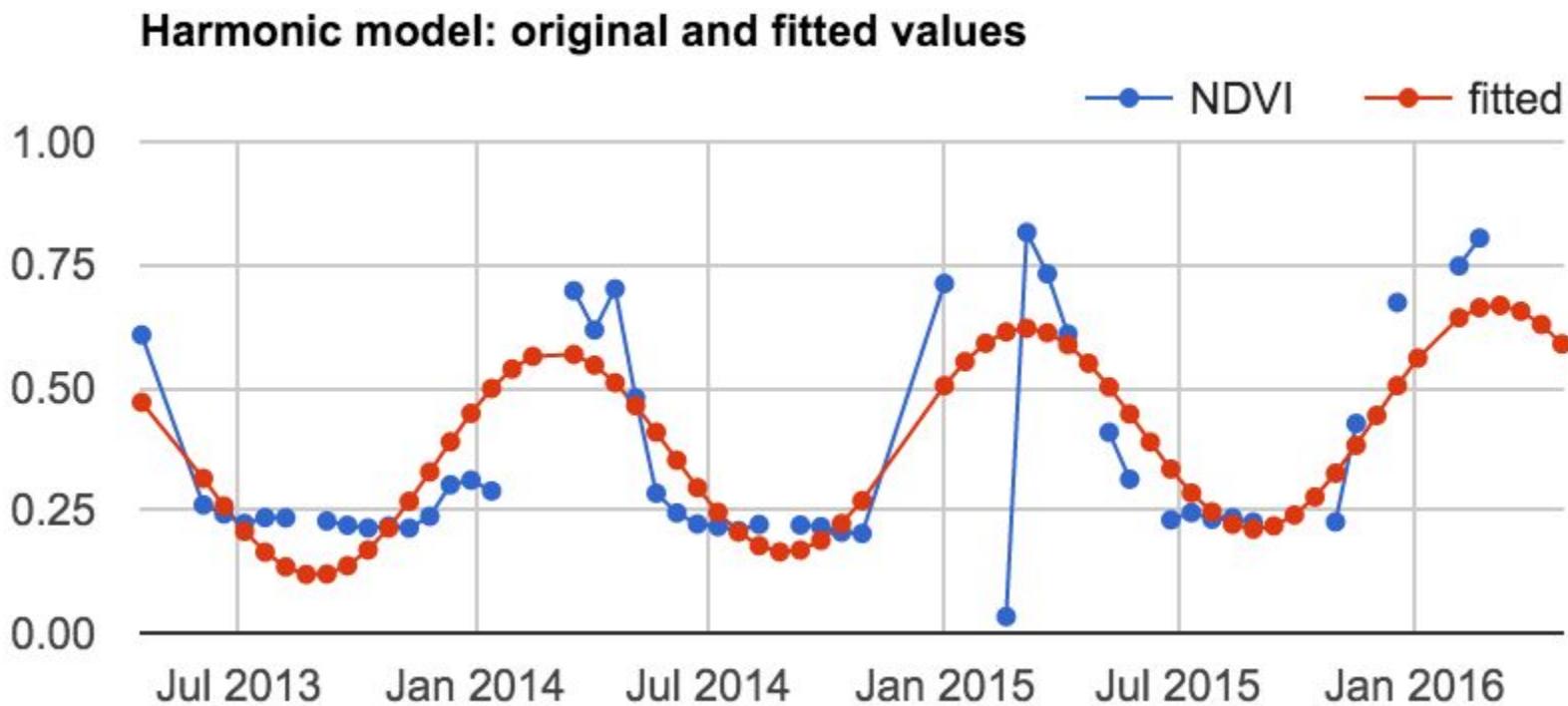
# Plug the coefficients into the linear model:

```
var harmonicTrendCoefficients = harmonicTrend.select('coefficients')
  .arrayProject([0])
  .arrayFlatten([harmonicIndependents]);
```

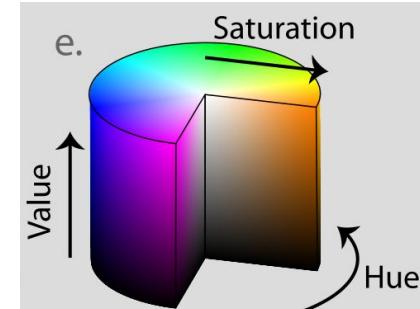
```
var fittedHarmonic = harmonicLandsat.map(function(image) {
  return image.addBands(
    image.select(harmonicIndependents)
      .multiply(harmonicTrendCoefficients)
      .reduce('sum')
      .rename('fitted'));
});
```

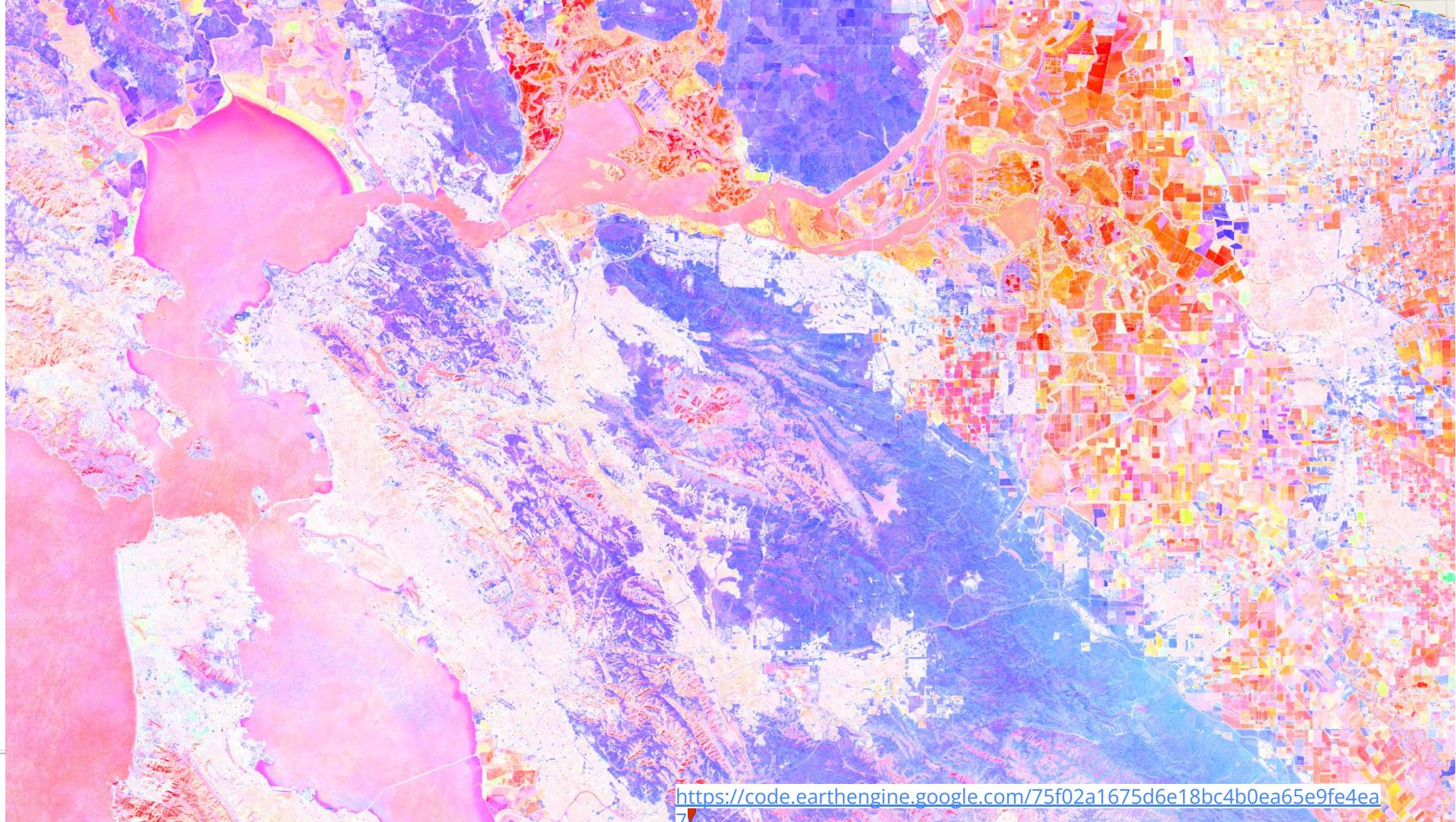
Plot the results:



# Map the results:

```
var phase = harmonicTrendCoefficients.select('cos').atan2(  
    harmonicTrendCoefficients.select('sin'));  
  
var amplitude = harmonicTrendCoefficients.select('cos').hypot(  
    harmonicTrendCoefficients.select('sin'));  
  
var rgb = phase.unitScale(-Math.PI, Math.PI).addBands( // hue  
    amplitude.multiply(2.5)).addBands( // saturation  
        ee.Image(1)).hsvToRgb(); // value  
  
Map.addLayer(rgb, {}, 'phase (hue), amplitude (saturation)');
```





<https://code.earthengine.google.com/75f02a1675d6e18bc4b0ea65e9fe4ea>

# Auto-covariance and Auto-correlation

Shumway and Stoffer (2016), equations 1.27, 1.26  
(assume stationarity):

$$\text{AutoCovariance} = \text{Cov}(p_t, p_{t-l}) = E[(p_t - E[p_t])(p_{t-l} - E[p_{t-l}])]$$

$$\begin{aligned}\text{AutoCorrelation} &= \text{Corr}(p_t, p_{t-l}) \\ &= \text{Cov}(p_t, p_{t-l}) / (\text{SD}(p_t)\text{SD}(p_{t-l}))\end{aligned}$$

$t$  = time

$p_t = NDVI_t$  = pixel value at time  $t$

$p_{t-l} = NDVI_{t-l}$  = pixel value at time  $t-l$

Get  $p_t$  and  $p_{t-l}$   
into the same  
collection  
with a join:

```
var lag = function(leftCollection, rightCollection, lagDays) {
  var filter = ee.Filter.and(
    ee.Filter.maxDifference({
      difference: 1000 * 60 * 60 * 24 * lagDays,
      leftField: timeField,
      rightField: timeField
    }),
    ee.Filter.greaterThan({
      leftField: timeField,
      rightField: timeField
    }));
  return ee.Join.saveAll({
    matchesKey: 'images',
    measureKey: 'delta_t',
    ordering: timeField,
    ascending: false, // Sort reverse chronologically
  }).apply({
    primary: leftCollection,
    secondary: rightCollection,
    condition: filter
  });
};
```

<https://code.earthengine.google.com/6b69374329dd43110cdd4c80d8d65784>

Join and add the lagged images as bands:

```
var lagged17 = lag(detrended, detrended, 17);

var merge = function(image) {
  var merger = function(current, previous) {
    return ee.Image(previous).addBands(current);
  };
  return ee.ImageCollection.fromImages(image.get('images')).iterate(merger, image);
};

var merged17 = ee.ImageCollection(lagged17.map(merge));
```

## Compute and display covariance:

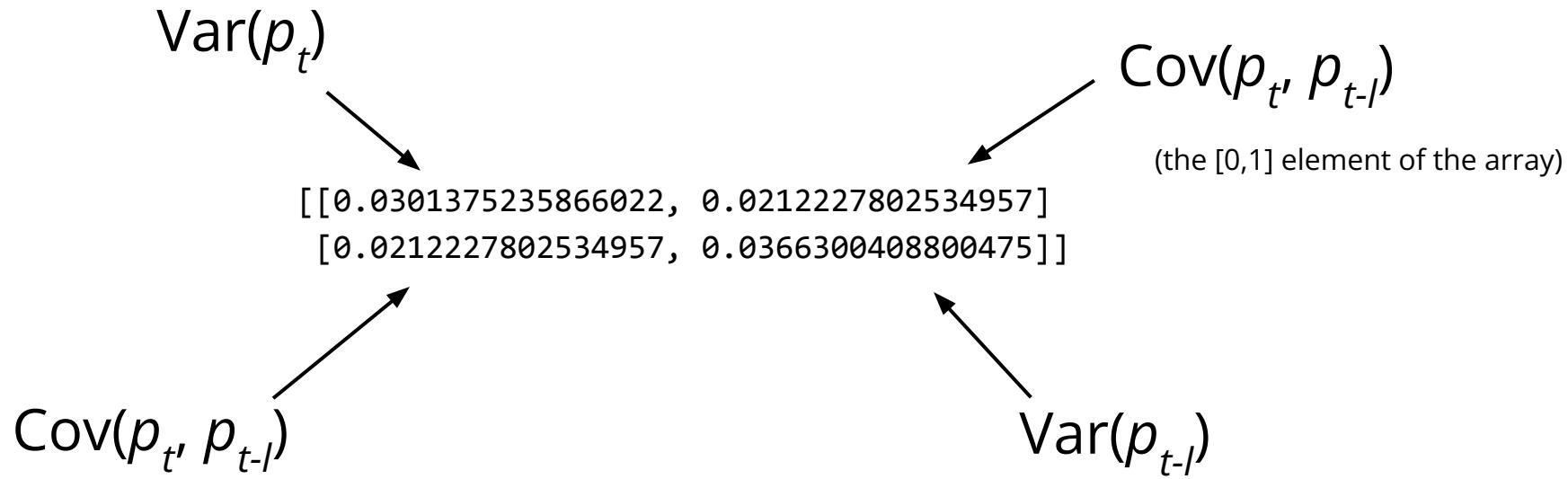
```
var covariance = function(mergedCollection, band, lagBand) {
  return mergedCollection.select([band, lagBand]).map(function(image) {
    return image.toArray();
  }).reduce(ee.Reducer.covariance(), 8);
};

var lagBand = dependent.cat('_1');

var covariance17 = ee.Image(covariance(merged17, dependent, lagBand));

Map.addLayer(covariance17.arrayGet([0, 1]), {}, 'covariance (lag = 17 days)');
```

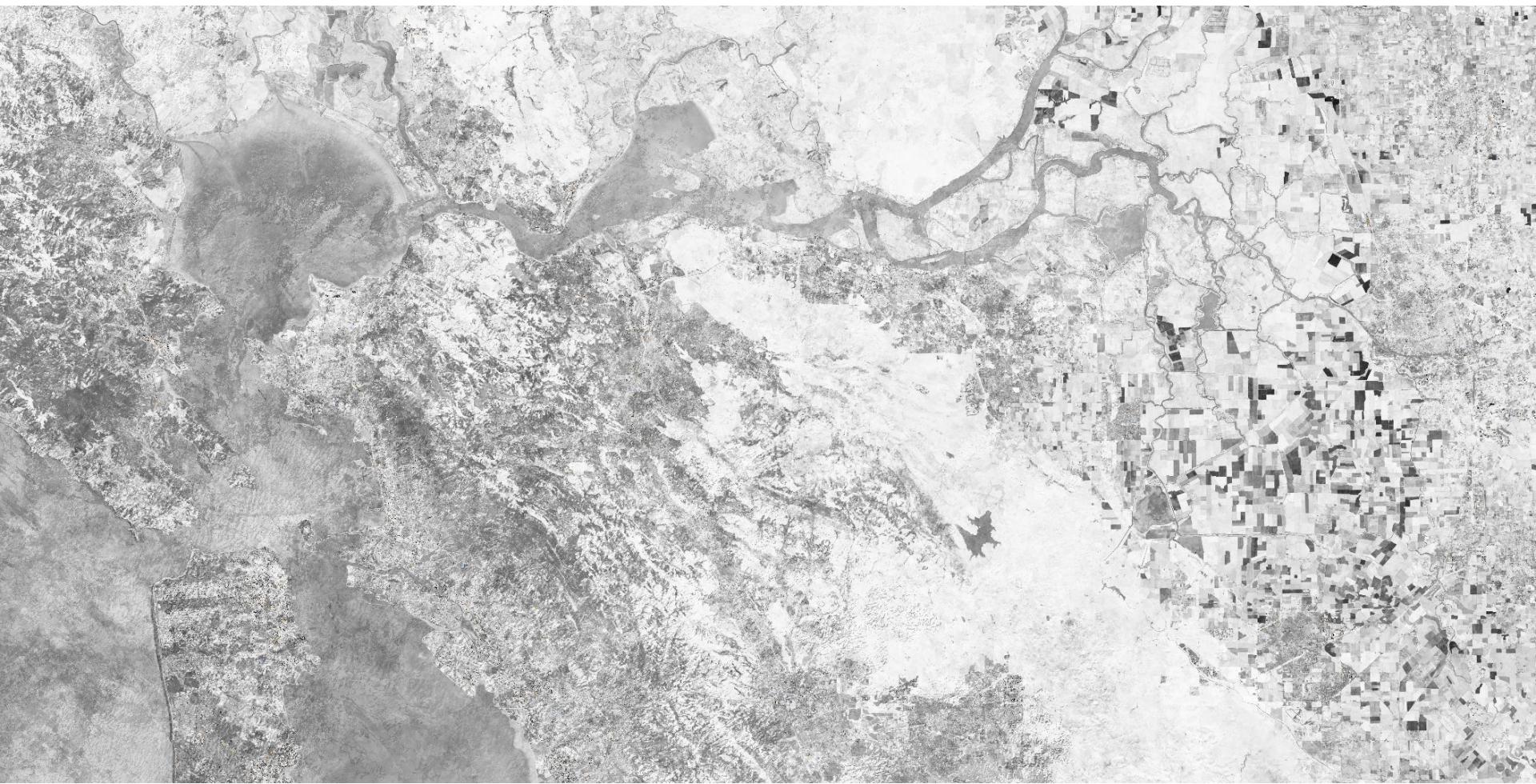
## Variance-Covariance matrix in a pixel (the ROI):





# Auto-correlation:

```
var correlation = function(vcArrayImage) {  
    var covariance = ee.Image(vcArrayImage).arrayGet([0, 1]);  
    var sd0 = ee.Image(vcArrayImage).arrayGet([0, 0]).sqrt();  
    var sd1 = ee.Image(vcArrayImage).arrayGet([1, 1]).sqrt();  
    return covariance.divide(sd0).divide(sd1).rename('correlation');  
};  
  
var correlation17 = correlation(covariance17);  
  
Map.addLayer(correlation17, {min: -1, max: 1}, 'correlation (lag = 17 days)');
```



# Cross-correlation



Shumway and Stoffer (2017), equations 1.30-1.31:

$$\text{CrossCovariance} = \text{Cov}(p_t, c_{t-l}) = E[(p_t - E[p_t])(c_{t-l} - E[c_{t-l}])]$$

$$\begin{aligned}\text{CrossCorrelation} &= \text{Corr}(p_t, c_{t-l}) \\ &= \text{Cov}(p_t, c_{t-l}) / (\text{SD}(p_t)\text{SD}(c_{t-l}))\end{aligned}$$

$t$  = time

$p_t$  =  $NDVI_t$  = pixel value at time  $t$

$c_{t-l}$  = covariate value at time  $t-l$

# Cross-covariance and cross-correlation:

```
// Precipitation (covariate)
var chirps = ee.ImageCollection('UCSB-CHG/CHIRPS/PENTAD');

// Join the t-1 (l = 1 pentad) precipitation images to the Landsat.
var lag1PrecipNDVI = lag(filteredLandsat, chirps, 5);

var merged1PrecipNDVI = ee.ImageCollection(lag1PrecipNDVI.map(merge));

var cov1PrecipNDVI = covariance(merged1PrecipNDVI, 'NDVI', 'precipitation');
Map.addLayer(cov1PrecipNDVI.arrayGet([0, 1]), {}, 'NDVI - PRECIP cov (lag = 5)');

var corr1PrecipNDVI = correlation(cov1PrecipNDVI);
Map.addLayer(corr1PrecipNDVI, {min: -0.5, max: 0.5}, 'NDVI - PRECIP corr (lag = 5)');
```



## Cross-covariance and cross-correlation, part 2:

```
// Join the precipitation images from the previous month
var lag30PrecipNDVI = lag(filteredLandsat, chirps, 30);

var sum30PrecipNDVI = ee.ImageCollection(lag30PrecipNDVI.map(function(image) {
  var laggedImages = ee.ImageCollection.fromImages(image.get('images'));
  return ee.Image(image).addBands(laggedImages.sum().rename('sum'));
}));

var cov30PrecipNDVI = covariance(sum30PrecipNDVI, 'NDVI', 'sum');
Map.addLayer(cov1PrecipNDVI.arrayGet([0, 1]), {}, 'NDVI - sum cov (lag = 30)');

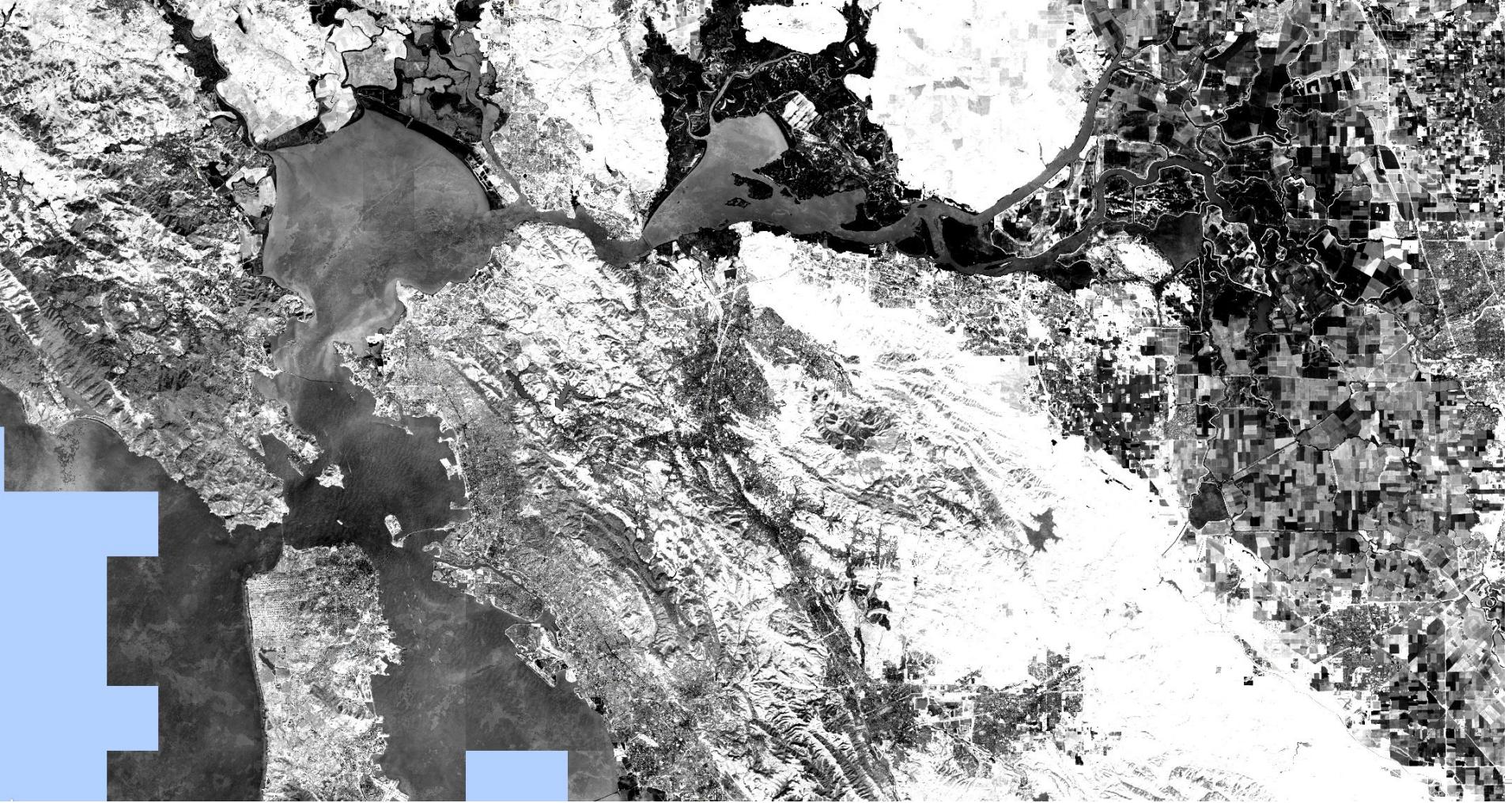
var corr30PrecipNDVI = correlation(cov30PrecipNDVI);
Map.addLayer(corr30PrecipNDVI, {min: -0.5, max: 0.5}, 'NDVI - sum corr (lag = 30)');
```

## Warning:

Shumway and Stoffer (2017), Example 1.26:

"...it is worthwhile to discuss the idea of **prewhitening** a series **prior to a cross-correlation** analysis. The basic idea is simple... at least one of the series must be white noise. If this is not the case, there is no simple way to tell if a cross-correlation estimate is significantly different from zero."





# Auto-regressive models



## Auto-regressive (AR) model:

$$p_t = \beta_0 + \beta_1 p_{t-1} + \beta_2 p_{t-2} + e_t$$

$p_t$  = NDVI at time  $t$

$t$  = time

$e_t$  = random error

We want  $\beta$ 's for every pixel...

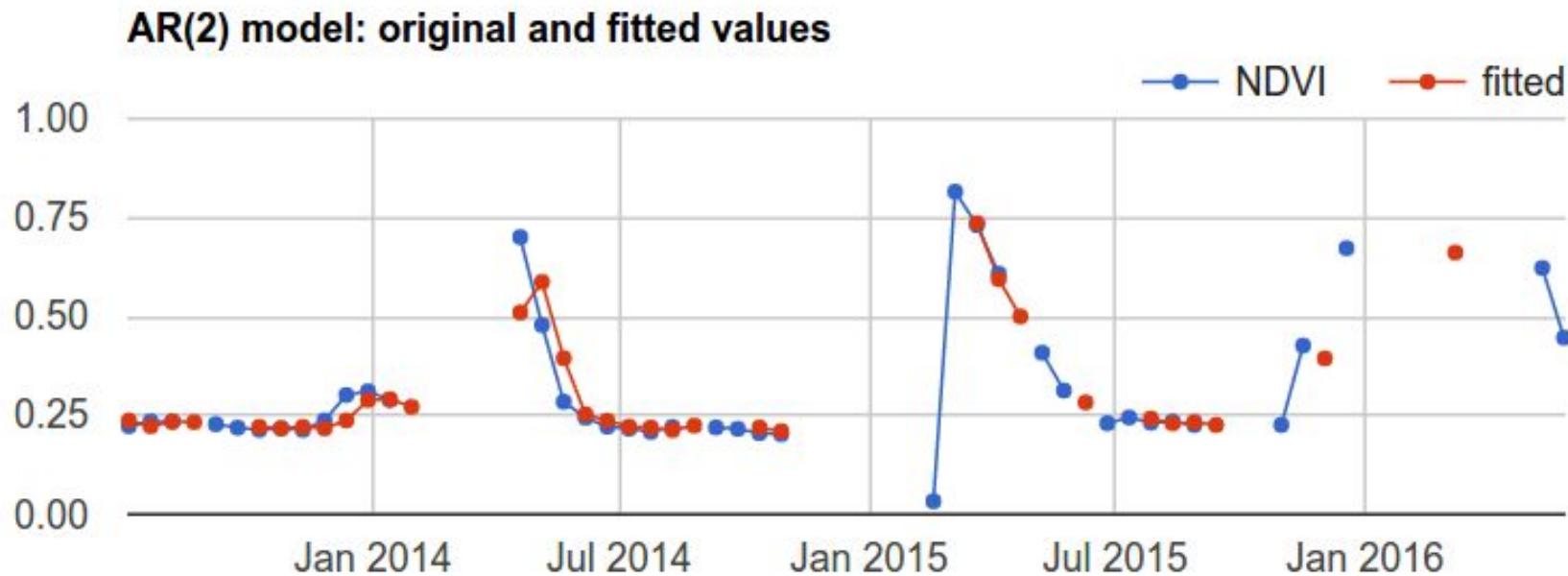
# AR model:

```
var lagged34 = ee.ImageCollection(lag(filteredLandsat, filteredLandsat, 34));  
  
var merged34 = lagged34.map(merge).map(function(image) {  
  return image.set('n', ee.List(image.get('images')).length());  
}).filter(ee.Filter.gt('n', 1));  
  
var arIndependents = ee.List(['constant', 'NDVI_1', 'NDVI_2']);  
  
var ar2 = merged34  
  .select(arIndependents.add(dependent))  
  .reduce(ee.Reducer.linearRegression(arIndependents.length(), 1));  
  
var arCoefficients = ar2.select('coefficients')  
  .arrayProject([0])  
  .arrayFlatten([arIndependents]);  
  
var fittedAR = merged34.map(function(image) {  
  return image.addBands(  
    image.expression('beta0 + beta1 * p1 + beta2 * p2', {  
      p1: image.select('NDVI_1'),  
      p2: image.select('NDVI_2'),  
      beta0: arCoefficients.select('constant'),  
      beta1: arCoefficients.select('NDVI_1'),  
      beta2: arCoefficients.select('NDVI_2')  
    }).rename('fitted'));  
});
```

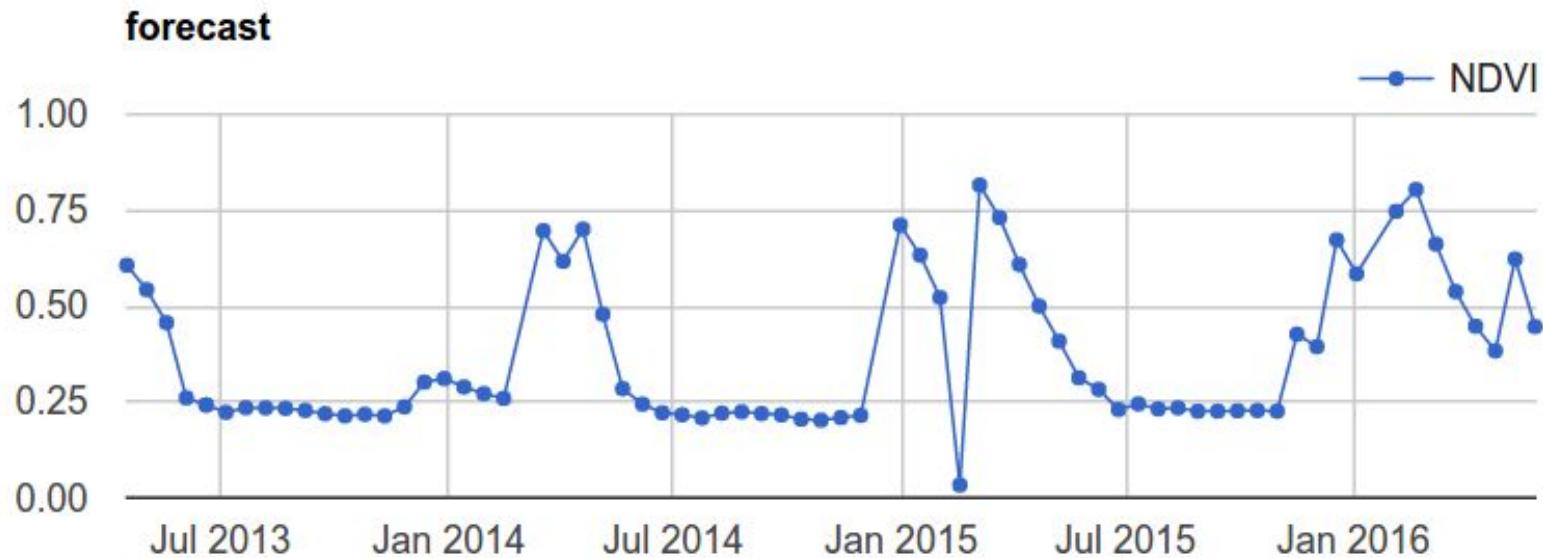
There's a problem here...

...missing data

Missing data:



## Filling in missing data and forecasting with an AR model.



# **Warning!** Here be dragons:

# Pop Quiz!

How would you implement smoothing?

# Smoothing

```
var join = ee.Join.saveAll({  
  matchesKey: 'images'  
});  
  
var diffFilter = ee.Filter.maxDifference({  
  difference: 1000 * 60 * 60 * 24 * 17,  
  leftField: timeField,  
  rightField: timeField  
});  
  
var threeNeighborJoin = join.apply({  
  primary: modeled,  
  secondary: modeled,  
  condition: diffFilter  
});  
  
var smoothed = ee.ImageCollection(threeNeighborJoin.map(function(image) {  
  var collection = ee.ImageCollection.fromImages(image.get('images'));  
  return ee.Image(image).addBands(collection.mean().rename('mean'));  
}));
```

# What will you create with Time Series?

[code.earthengine.google.com](https://code.earthengine.google.com)