



MCMC I for Infectious Diseases

Lab & Activity

Resources

Presentation Activity



PollEv.com/amandableichrodt759

Toolbox Code



https://github.com/gchowell/paramEstimation_forecasting_ODEmodels

Toolbox Tutorial



<https://pubmed.ncbi.nlm.nih.gov/38378161/>

Emory's Apporto

<https://rsphemory.apporto.com/>





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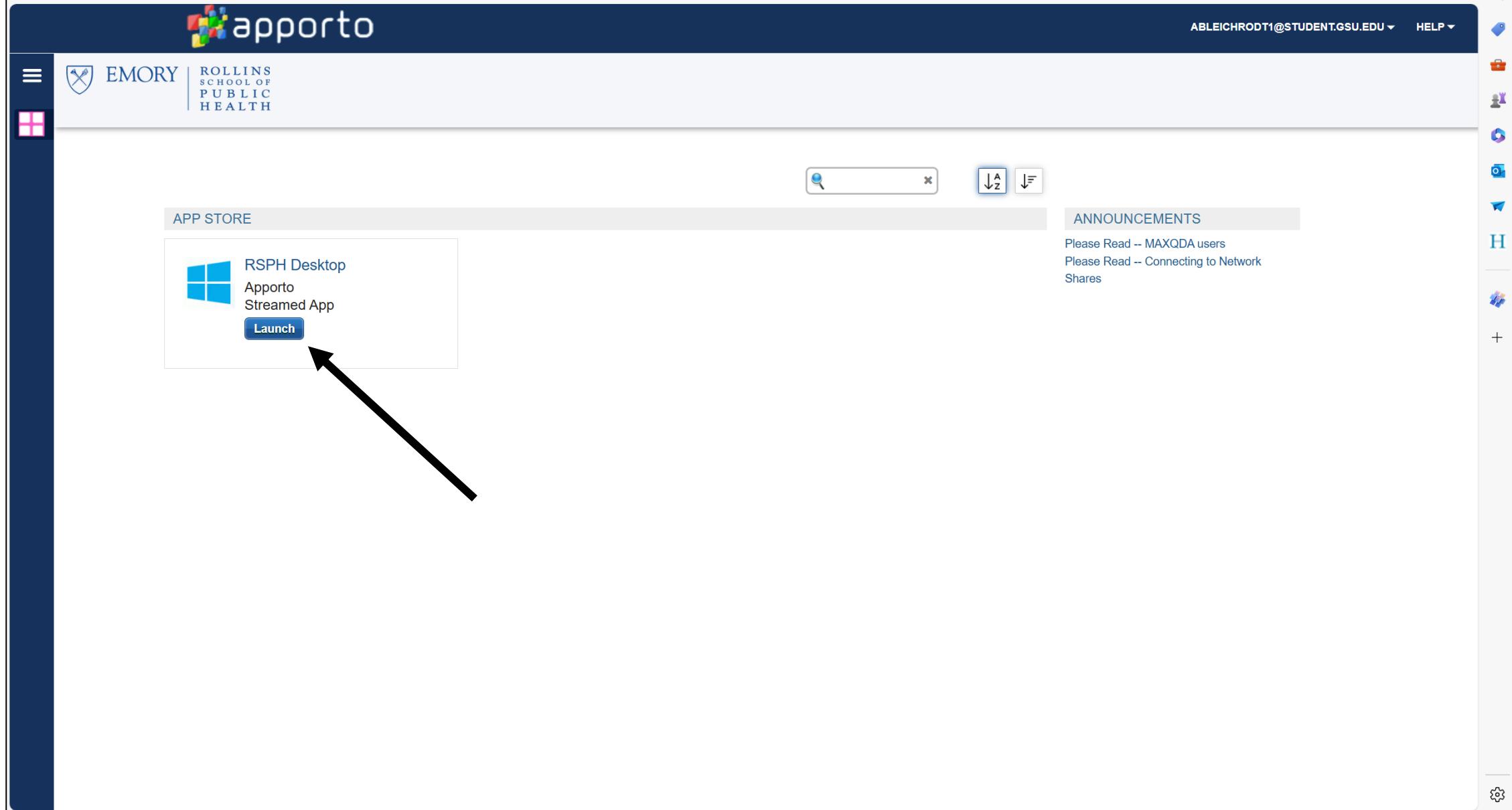
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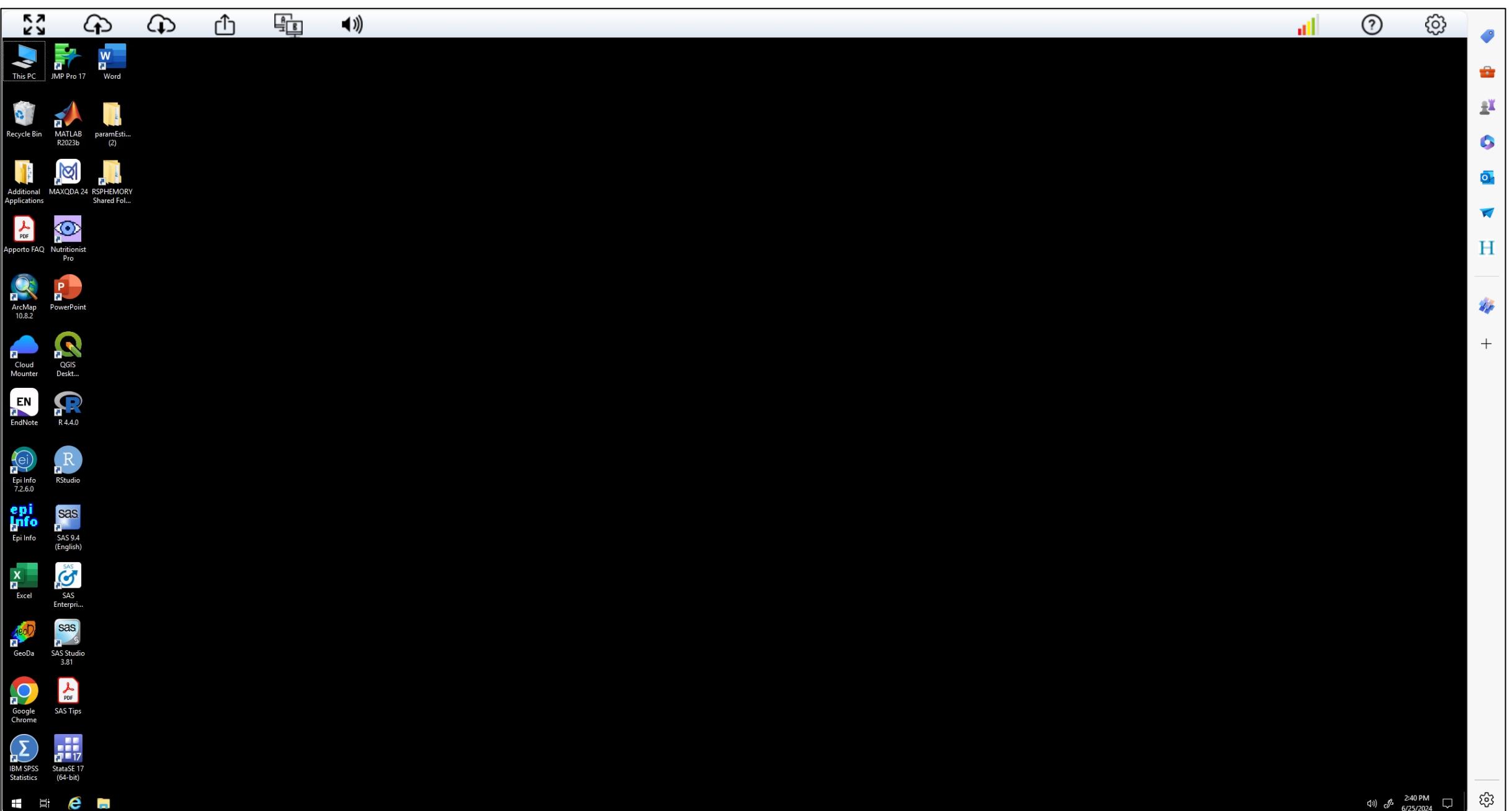
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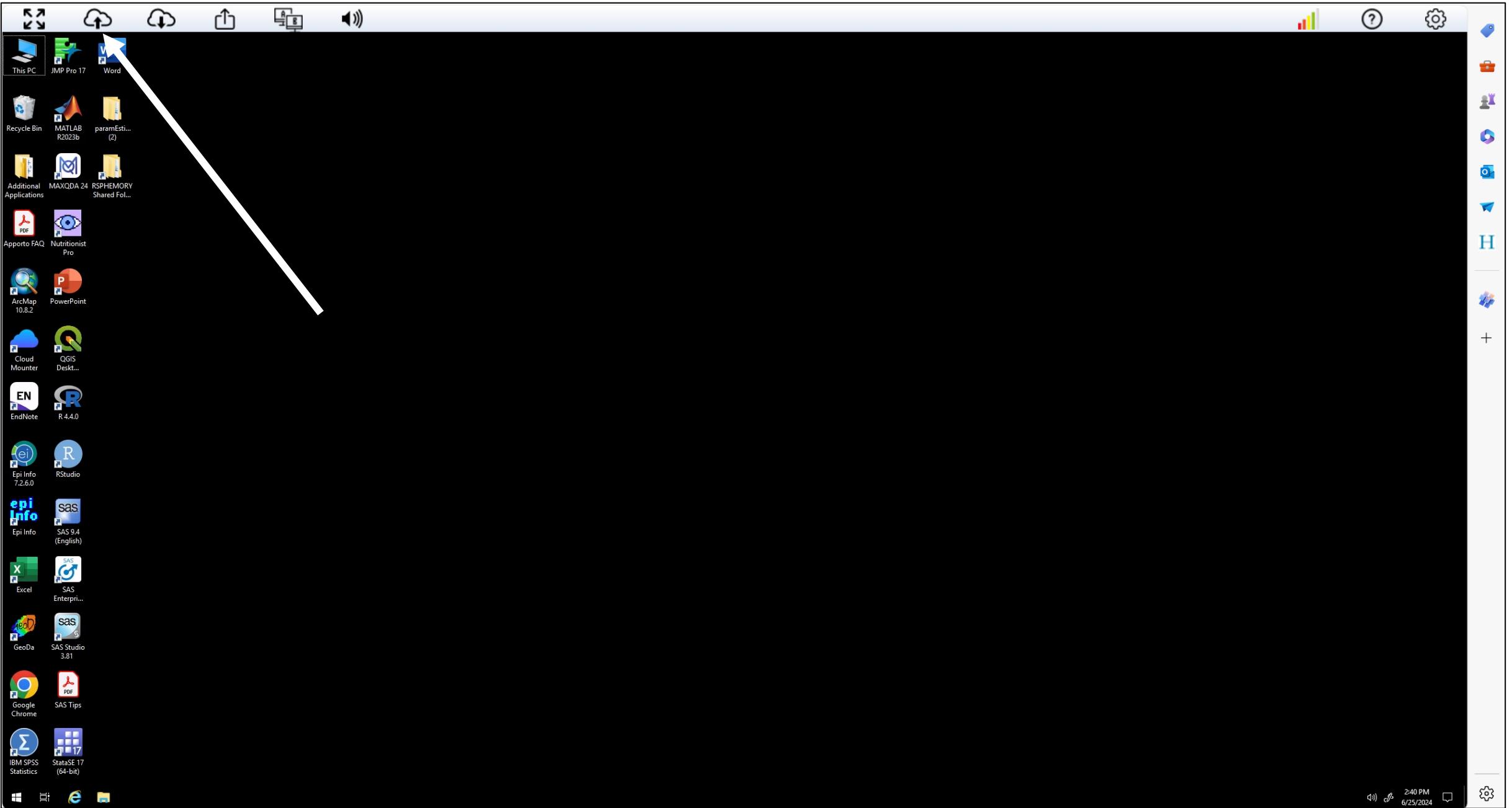
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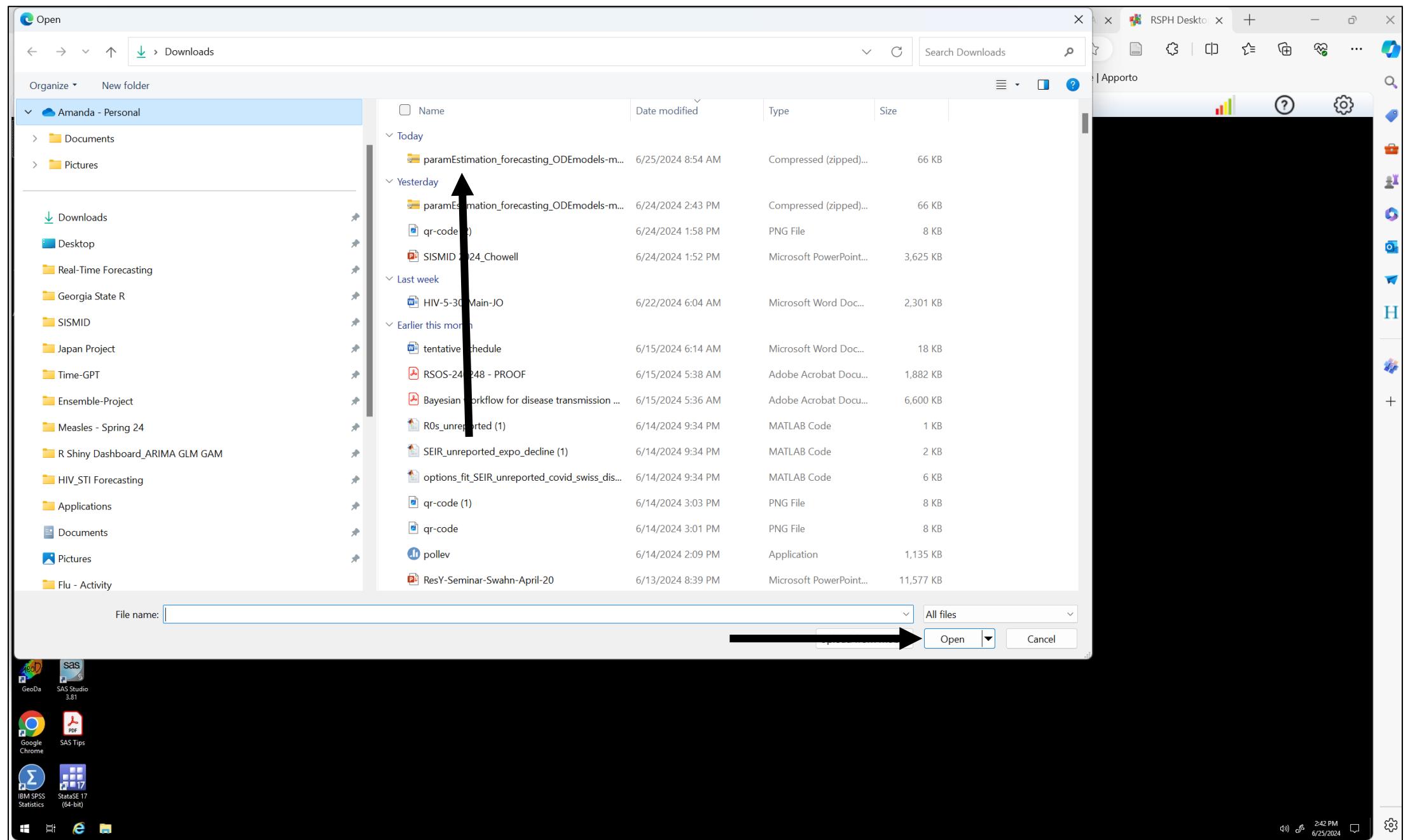




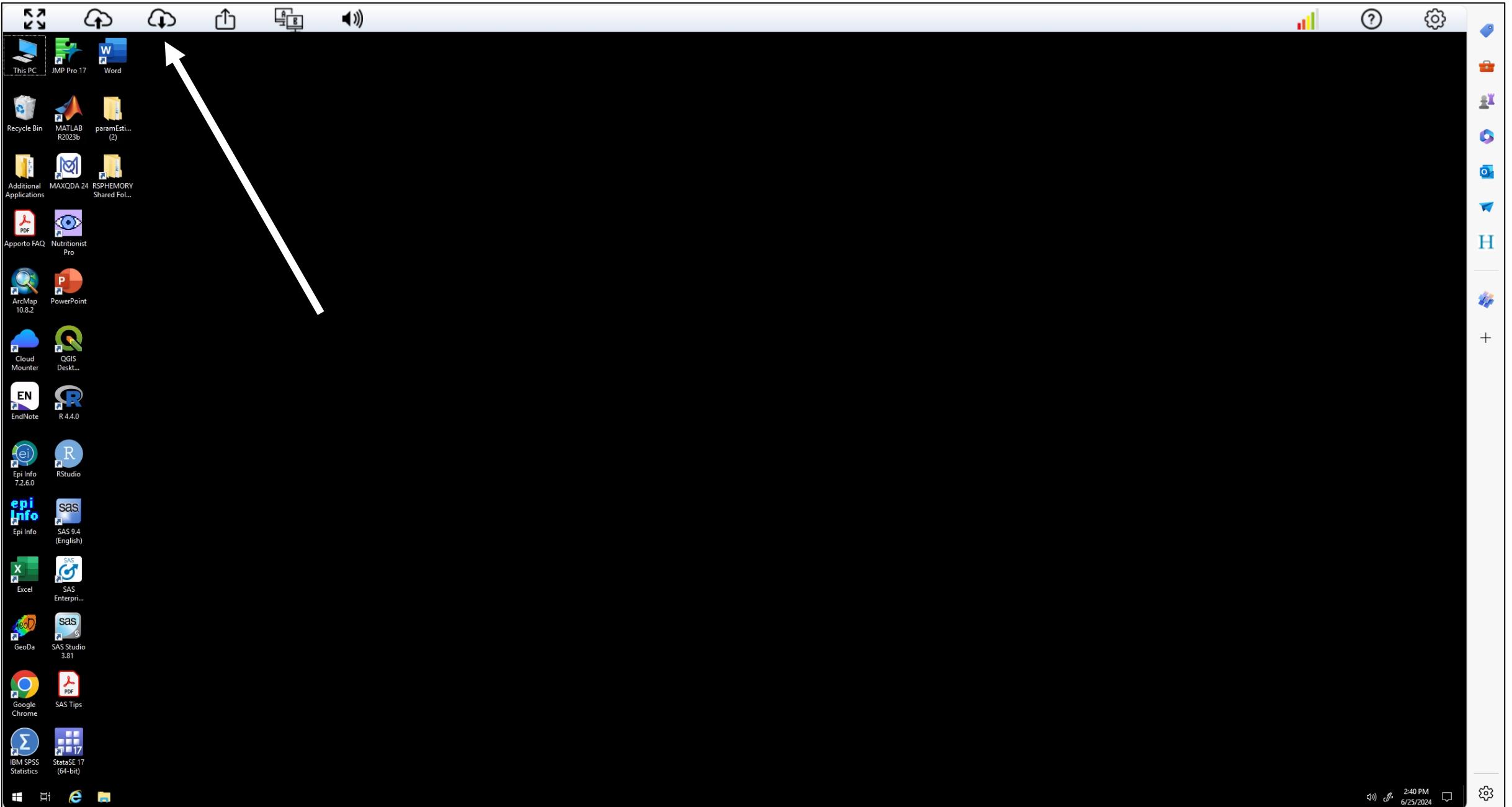


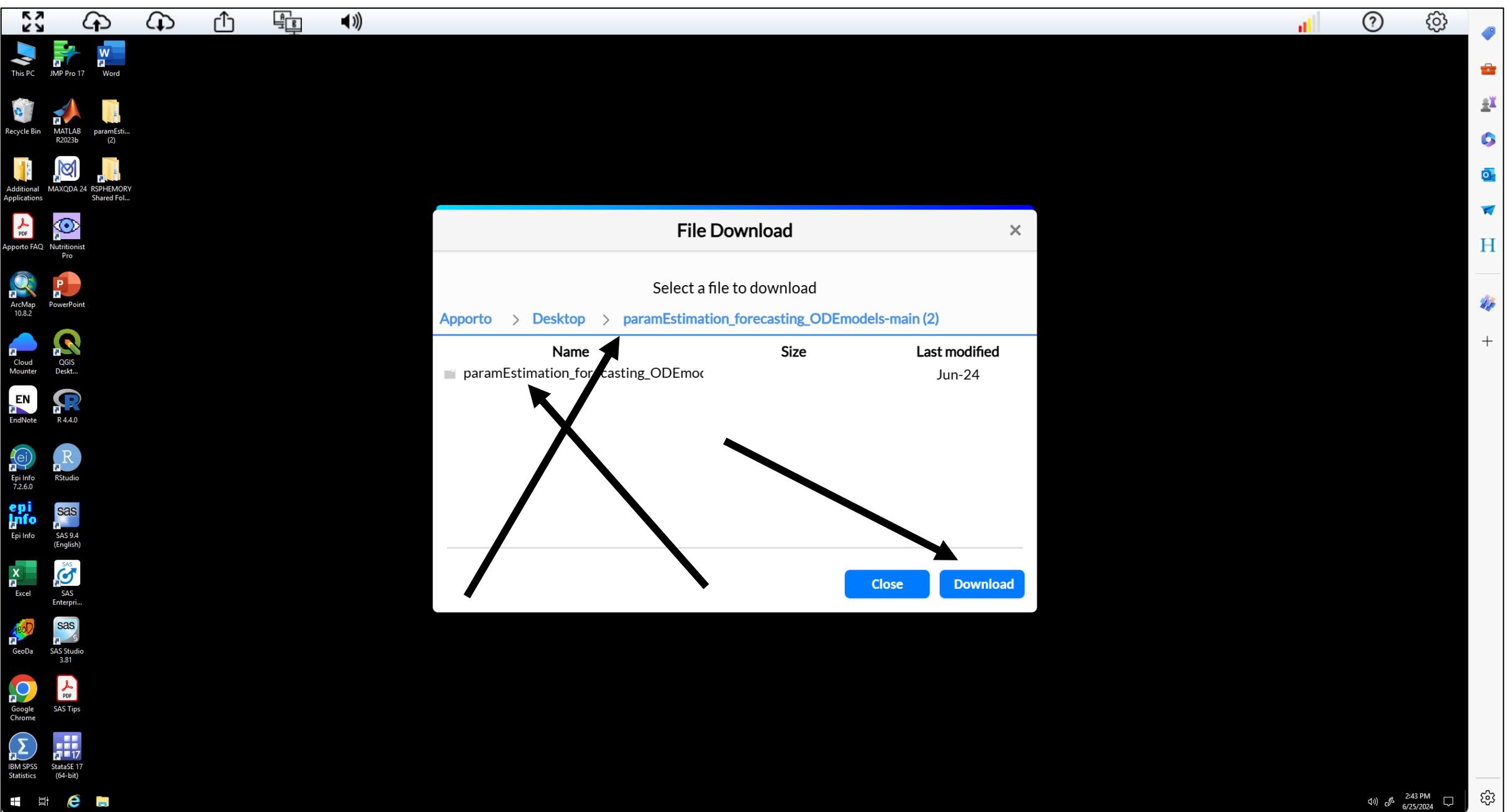
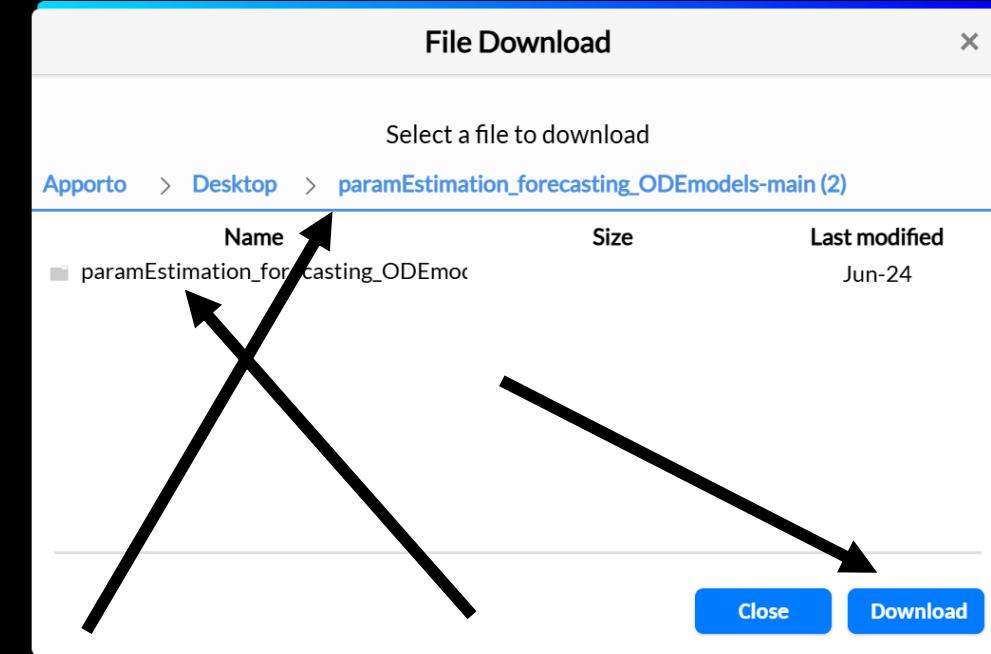
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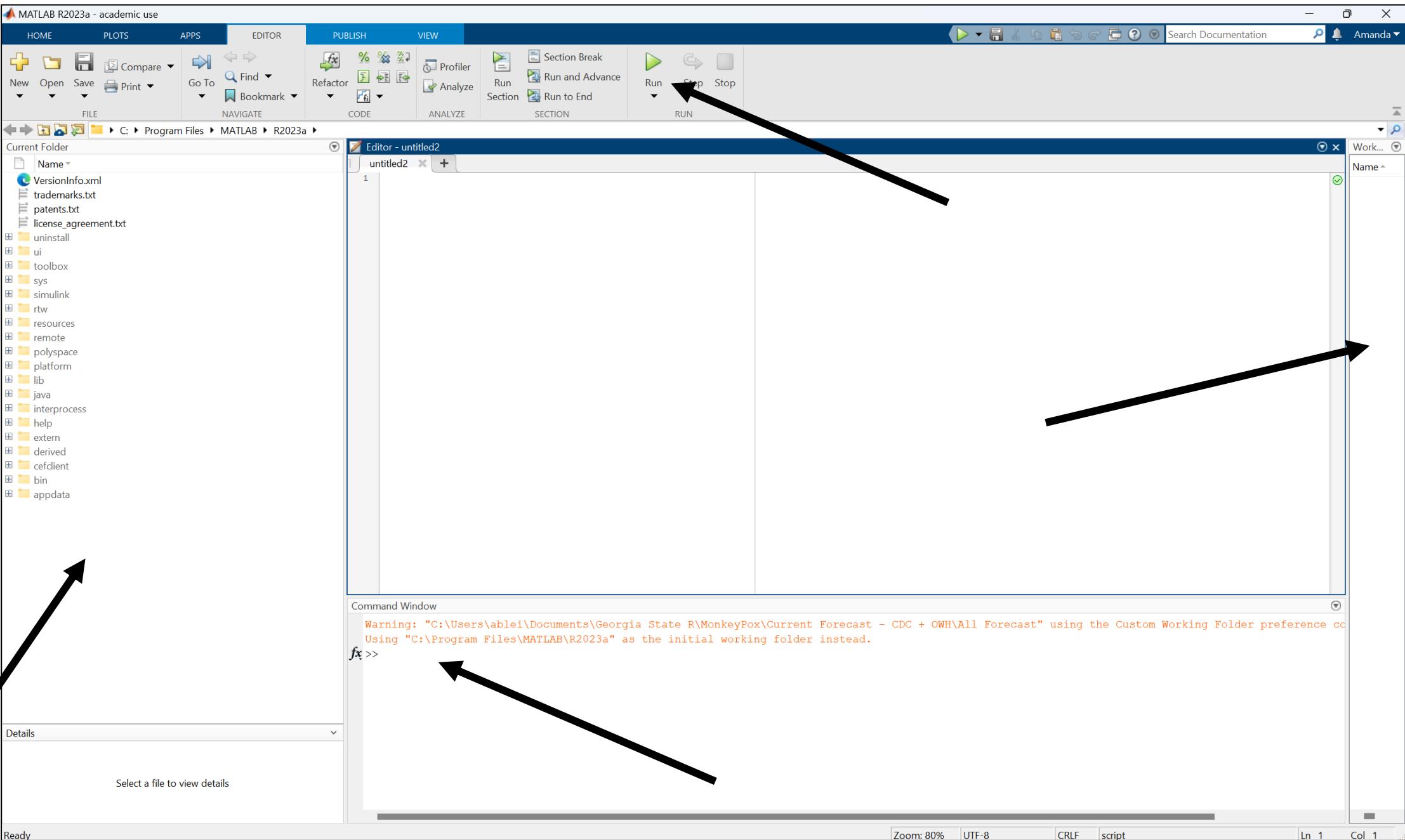


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Exploring MATLAB



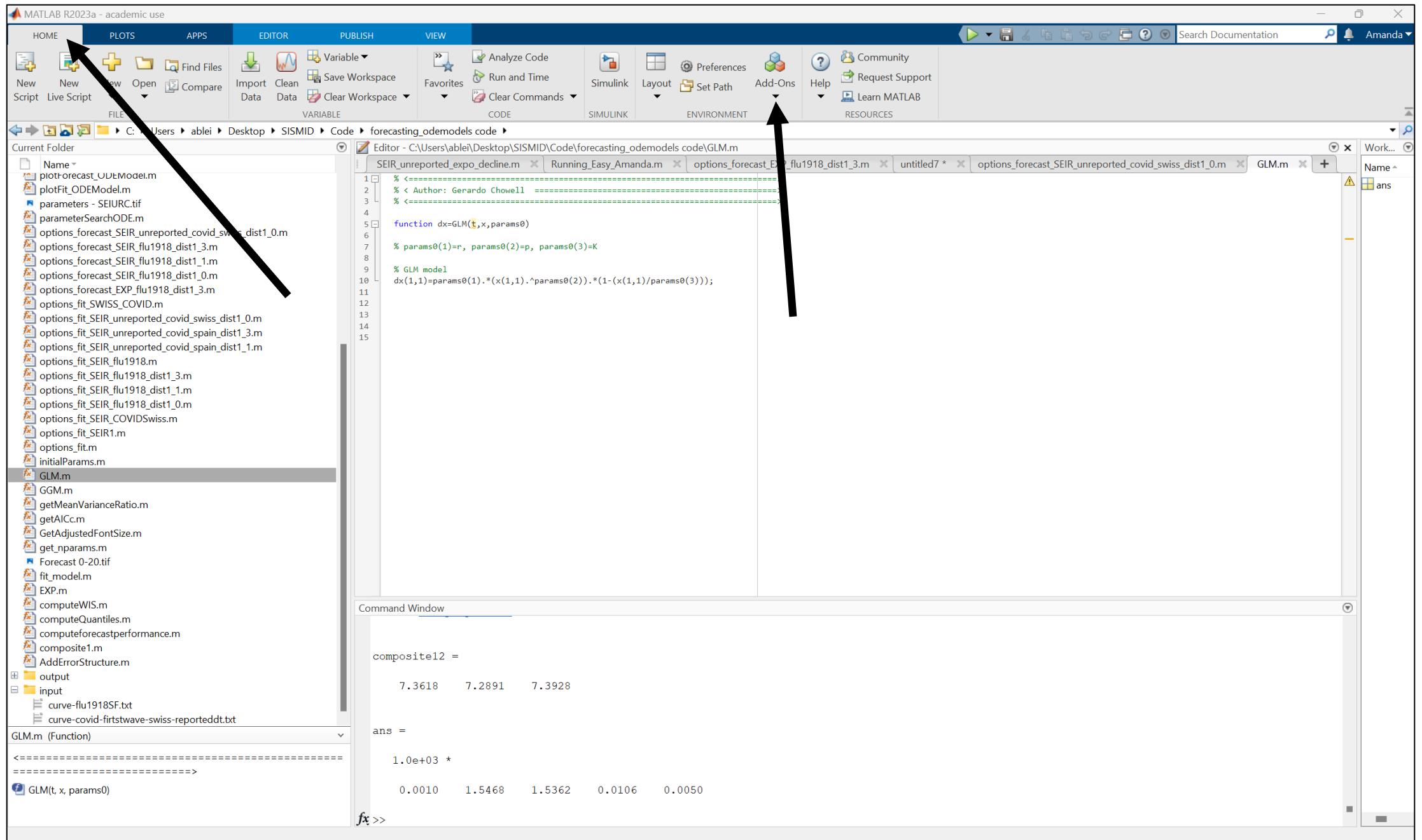
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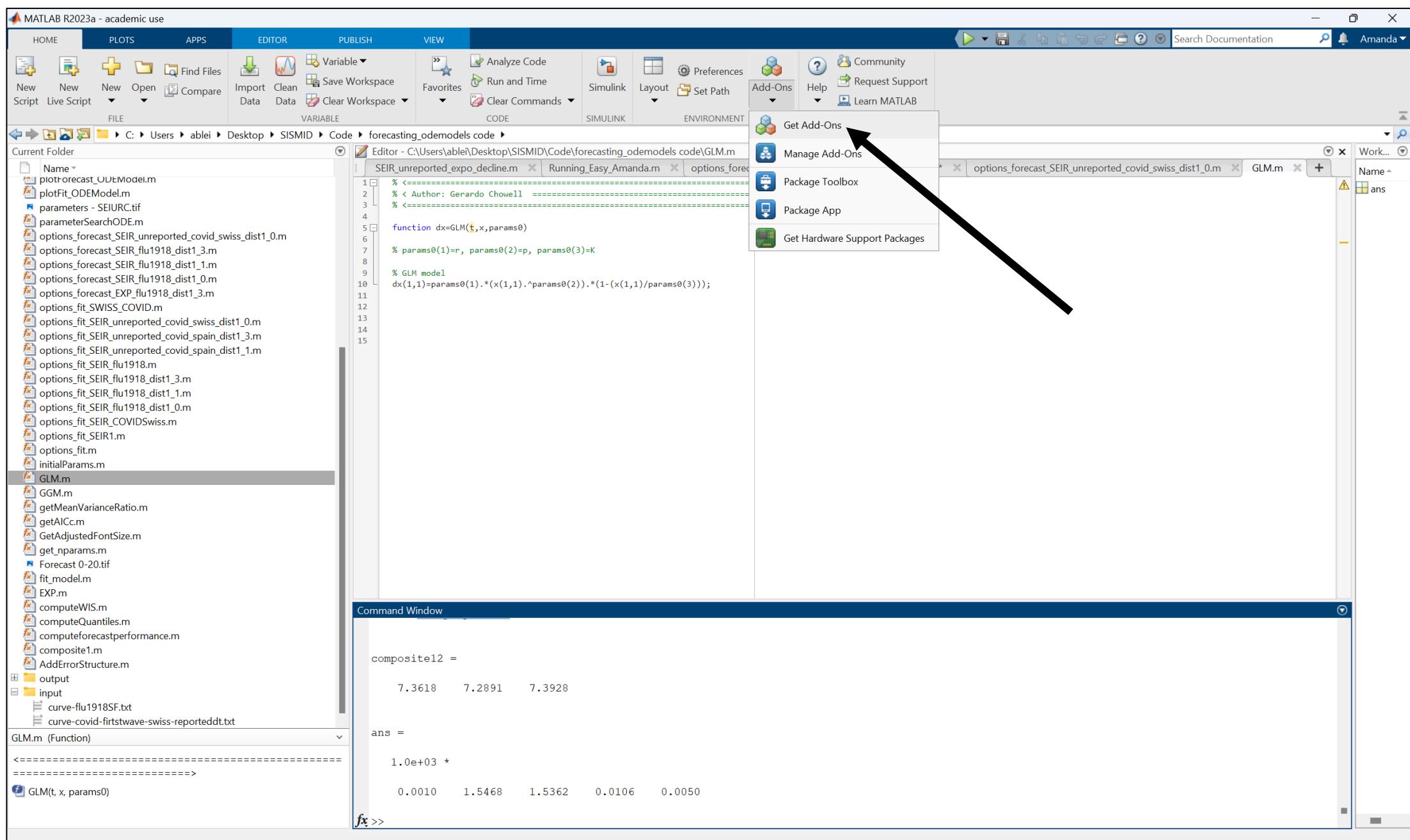
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Curve Fitting Toolbox
Global Optimization Toolbox
Optimization Toolbox
Signal Processing Toolbox
Simulink
Statistics and Machine Learning Toolbox

Needed Folders
<i>input</i>
<i>output</i>

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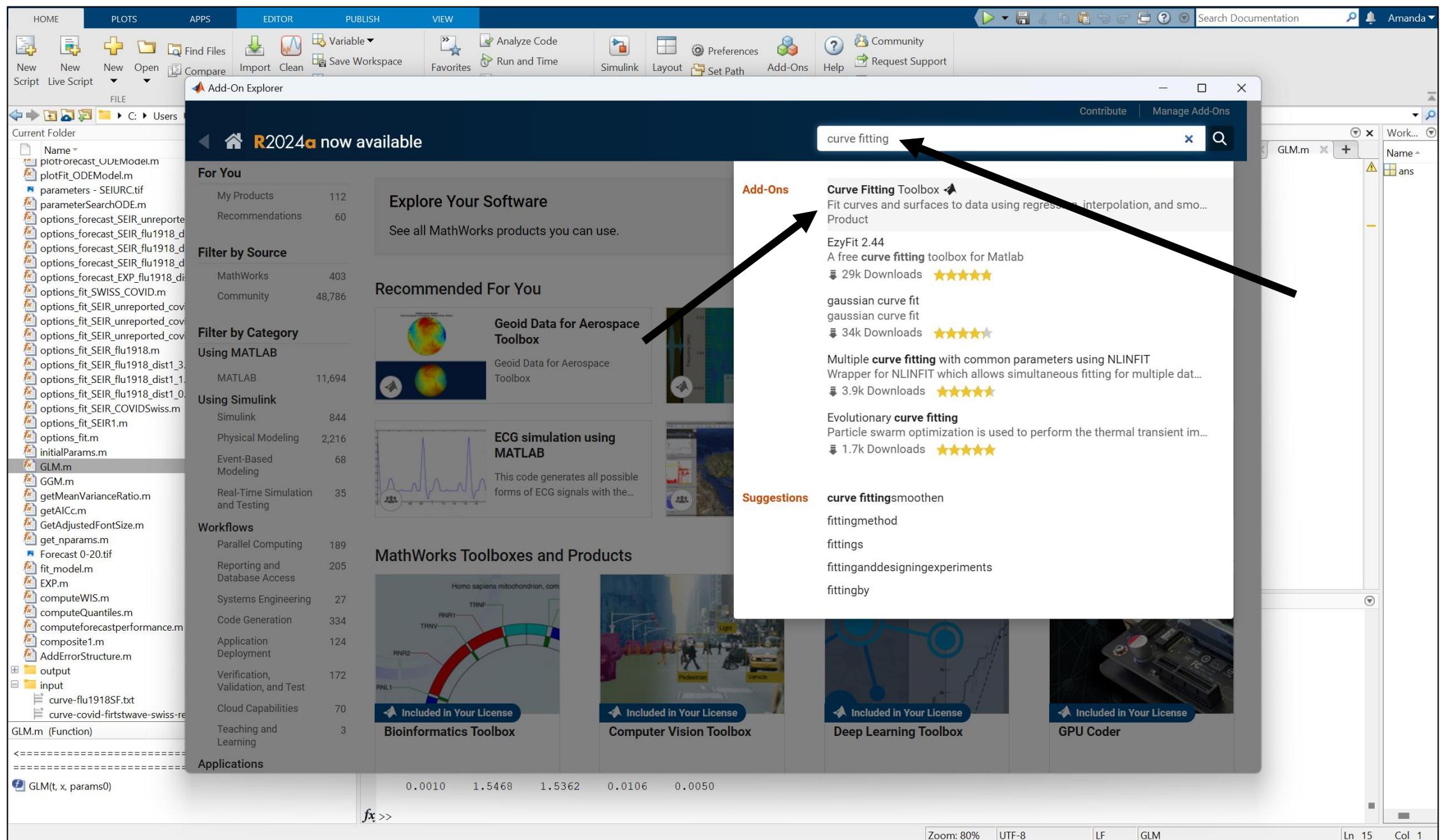
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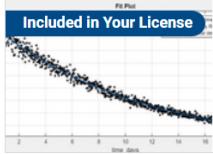
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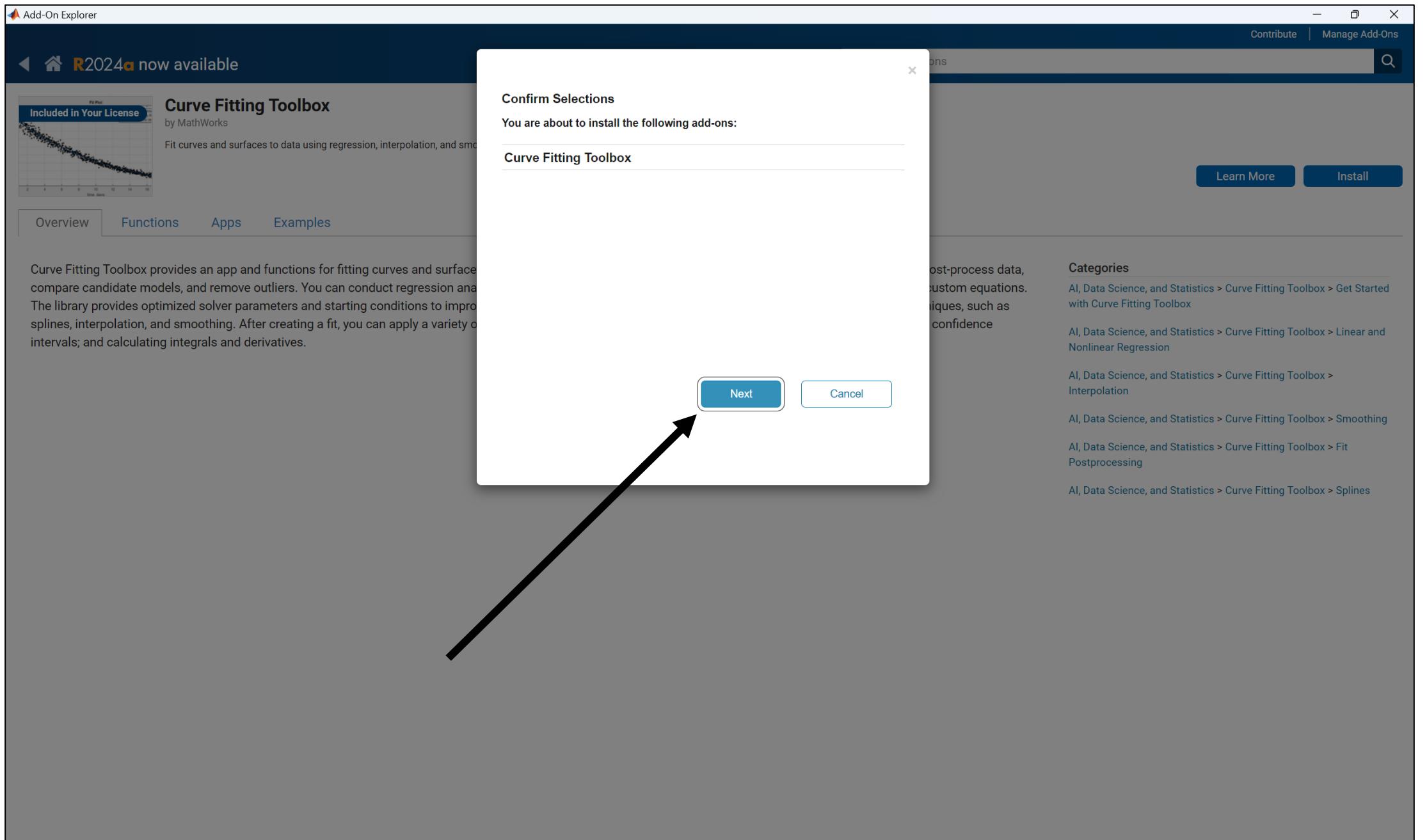
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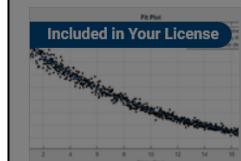
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Overview Functions Apps Examples

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post-process data, such as custom equations. The library provides optimized solver parameters and starting conditions to improve performance. It includes functions for fitting splines, interpolation, and smoothing. After creating a fit, you can apply a variety of post-processing techniques, such as confidence intervals; and calculating integrals and derivatives.

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The *QuantDiffForecast* Toolbox

Multiple parameter estimation options

- Estimation: NLSQ & MLE
- Error distributions: Normal, Poisson, and four variations of negative binomial
- Bootstrapping and number of initial guesses

Flexible model specifications

- User specified system of ODEs
 - Initial parameter and state variable conditions
 - Estimation of composite function(s) from the specified model parameters

Evaluation of bootstrapping error, model fit and forecasting performance

- Mean Squared Error (MSE)
- Mean Absolute Error (MAE)
- Weighted Interval Scores (WIS)
- 95% PI Coverage
- Monte Carlo Squared Error (MCSE)

Downloading the Toolbox

https://github.com/gchowell/paramEstimation_forecasting_ODEmodels

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QuantDiffForecast

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Video tutorial: <https://www.youtube.com/watch?v=eyyX63H12sY&t=41s>

It carries out the following tasks:

- fitting ODE models to time series data,
- estimation of model parameters with quantified uncertainty, Monte Carlo standard errors (MCSES),
- plotting the best fit of the ODE model, calibration performance metrics, and empirical distribution of the parameters
- plotting forecasts from the best-fit model and performance metrics of the forecasts,
- conducts rolling window analyses of parameter estimates for specific periods and window sizes

About

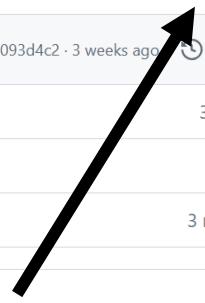
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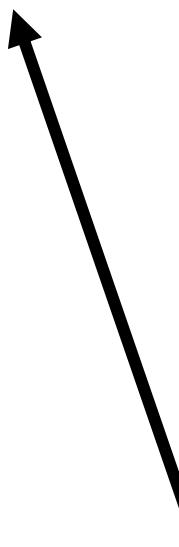
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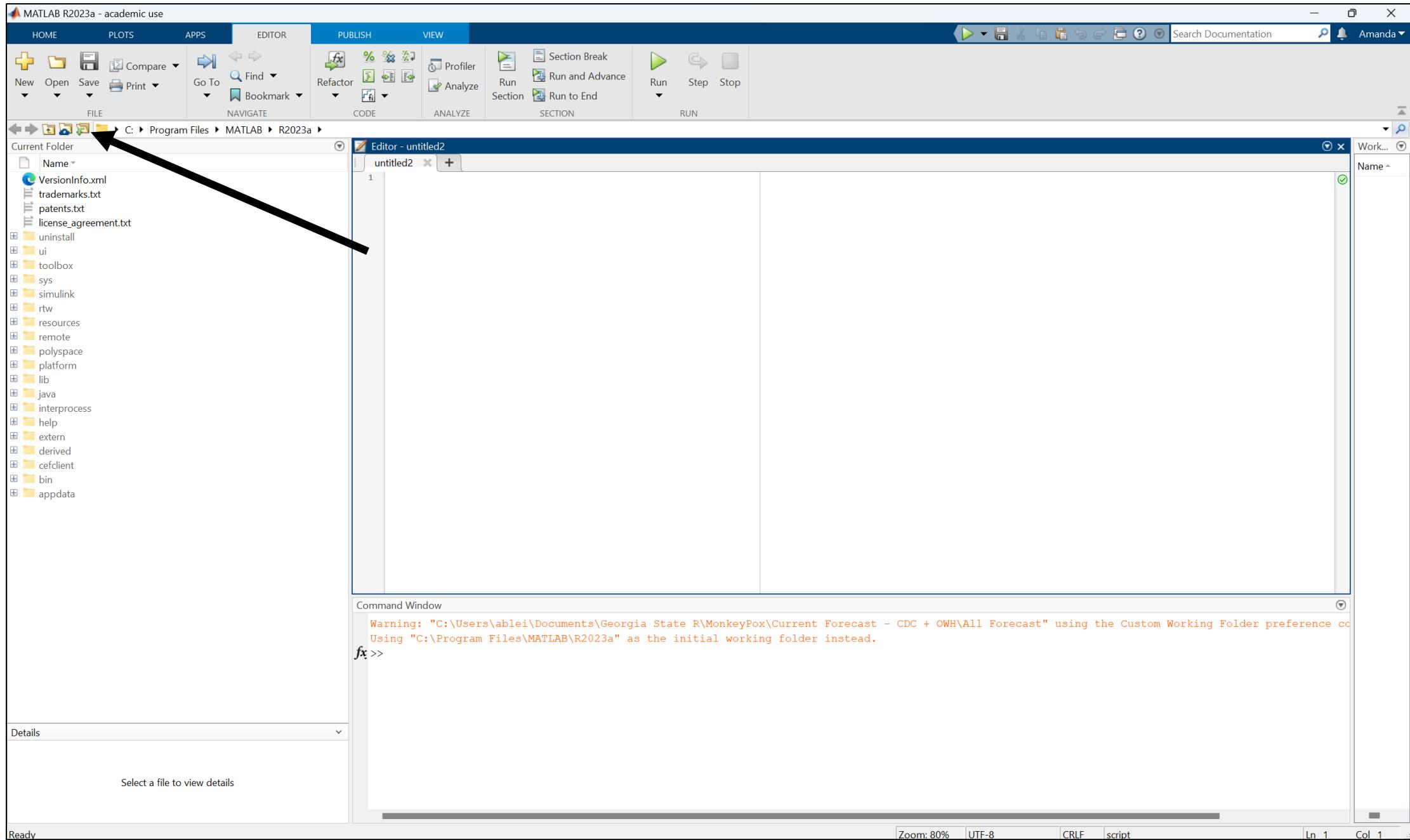


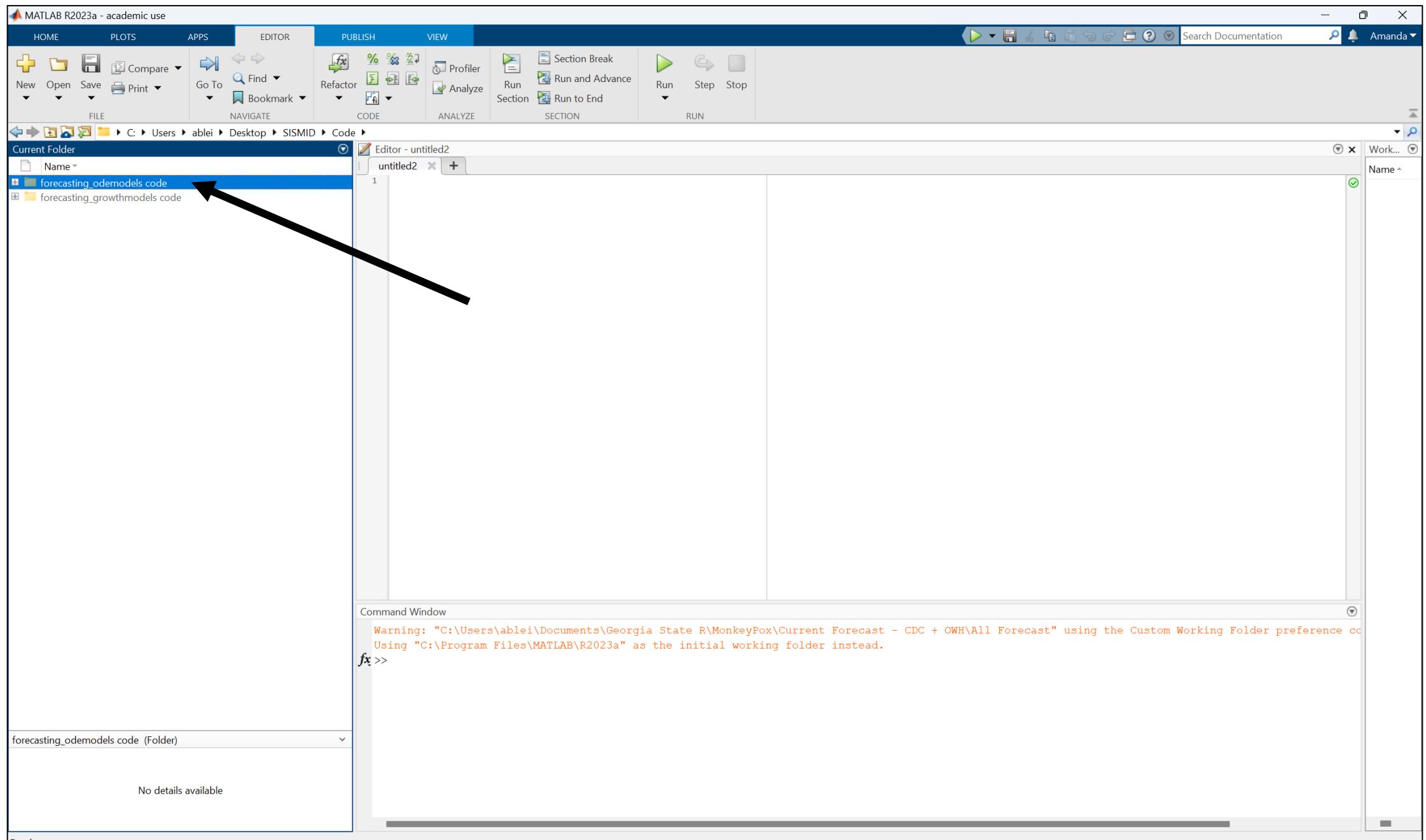
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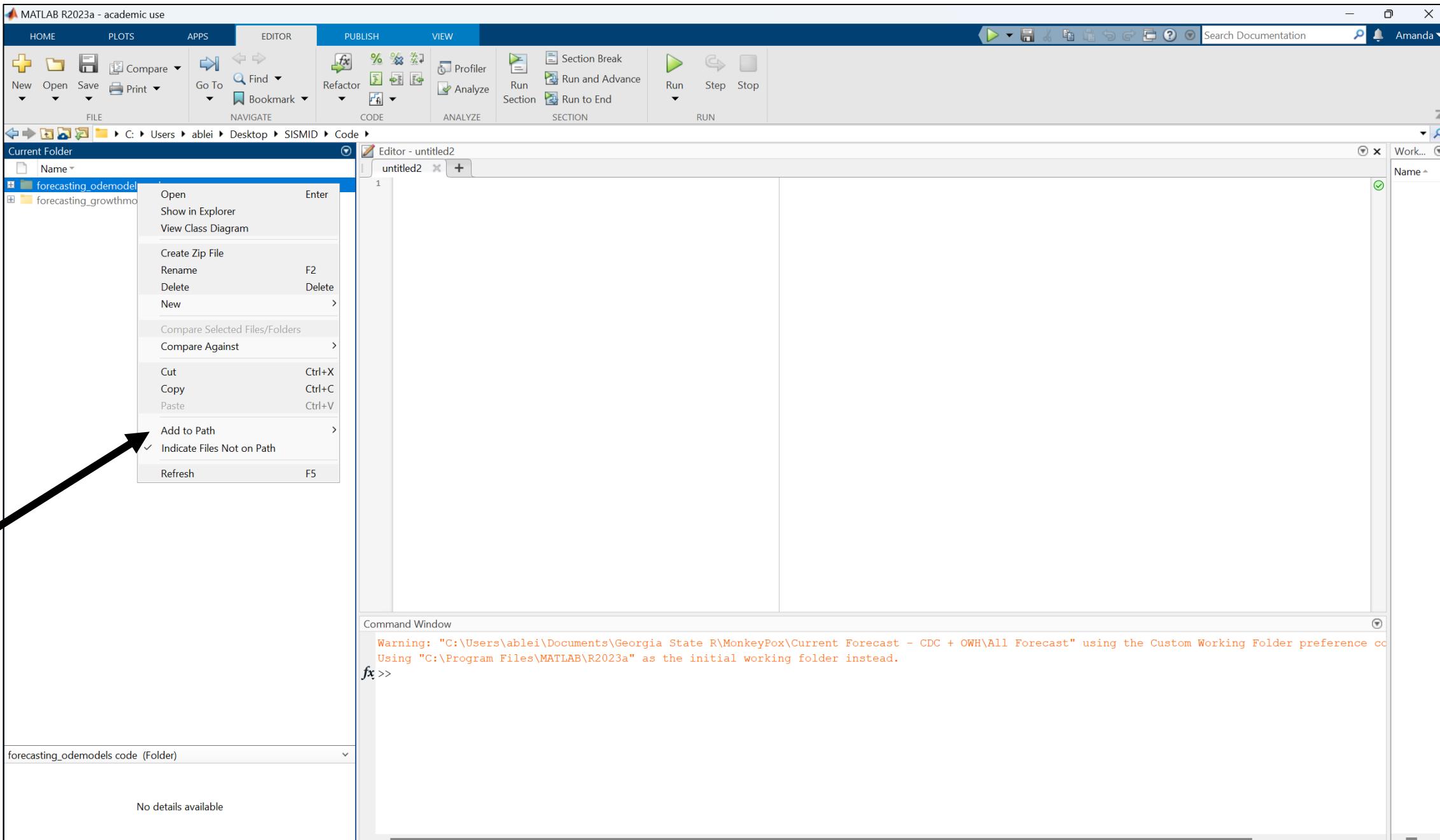


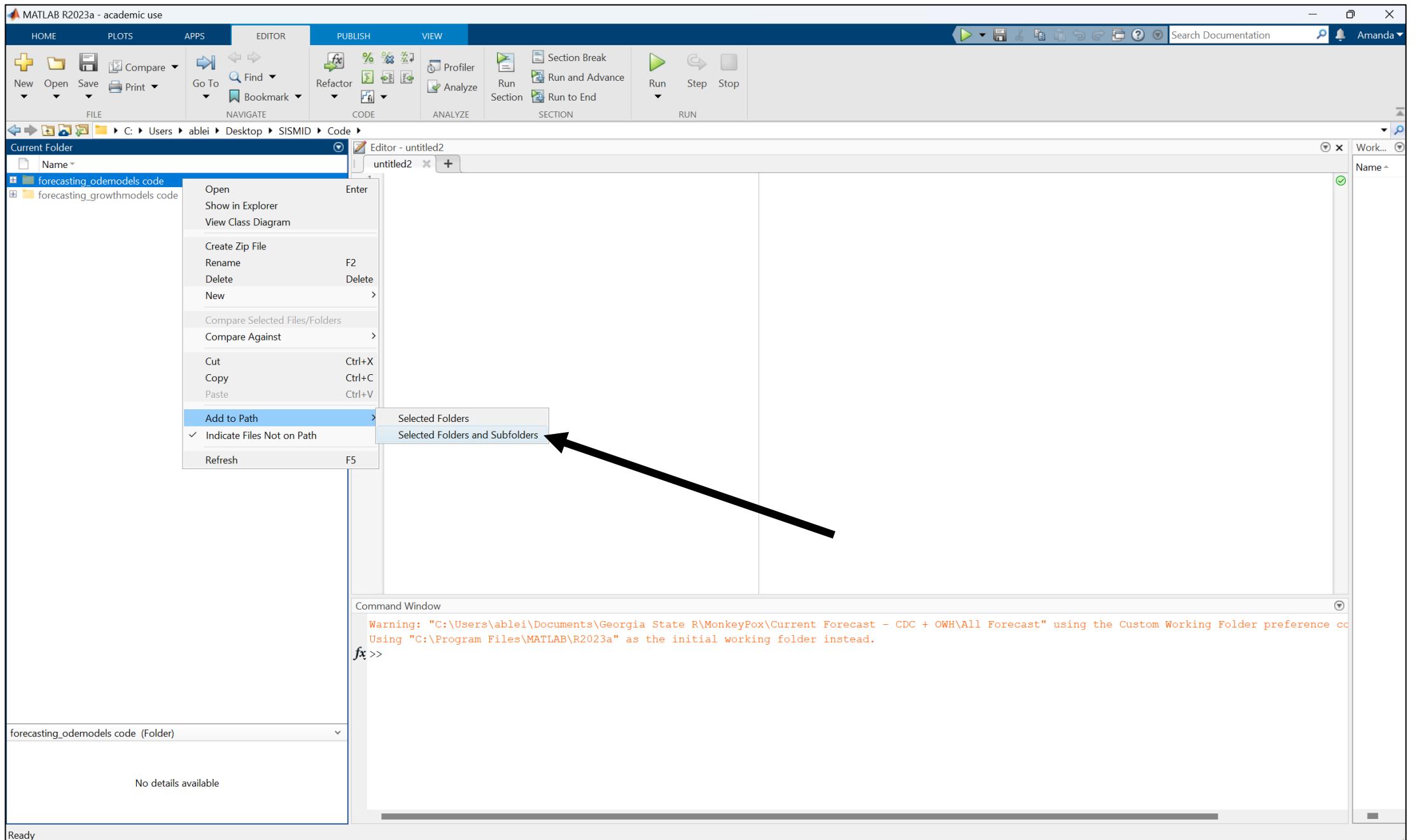
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options_fit_SEIR_flu1918	MATLAB Code	2 KB	No	6 KB	70%	6/6/2024 9:52 AM
options_fit_SEIR_flu1918_dist1_0	MATLAB Code	2 KB	No	6 KB	70%	6/6/2024 9:52 AM
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Setting up the Working Directory



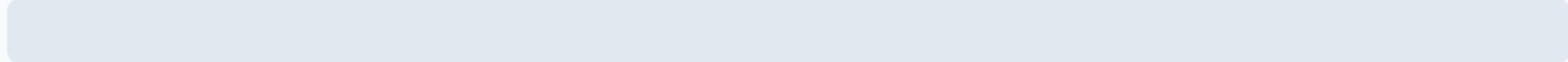






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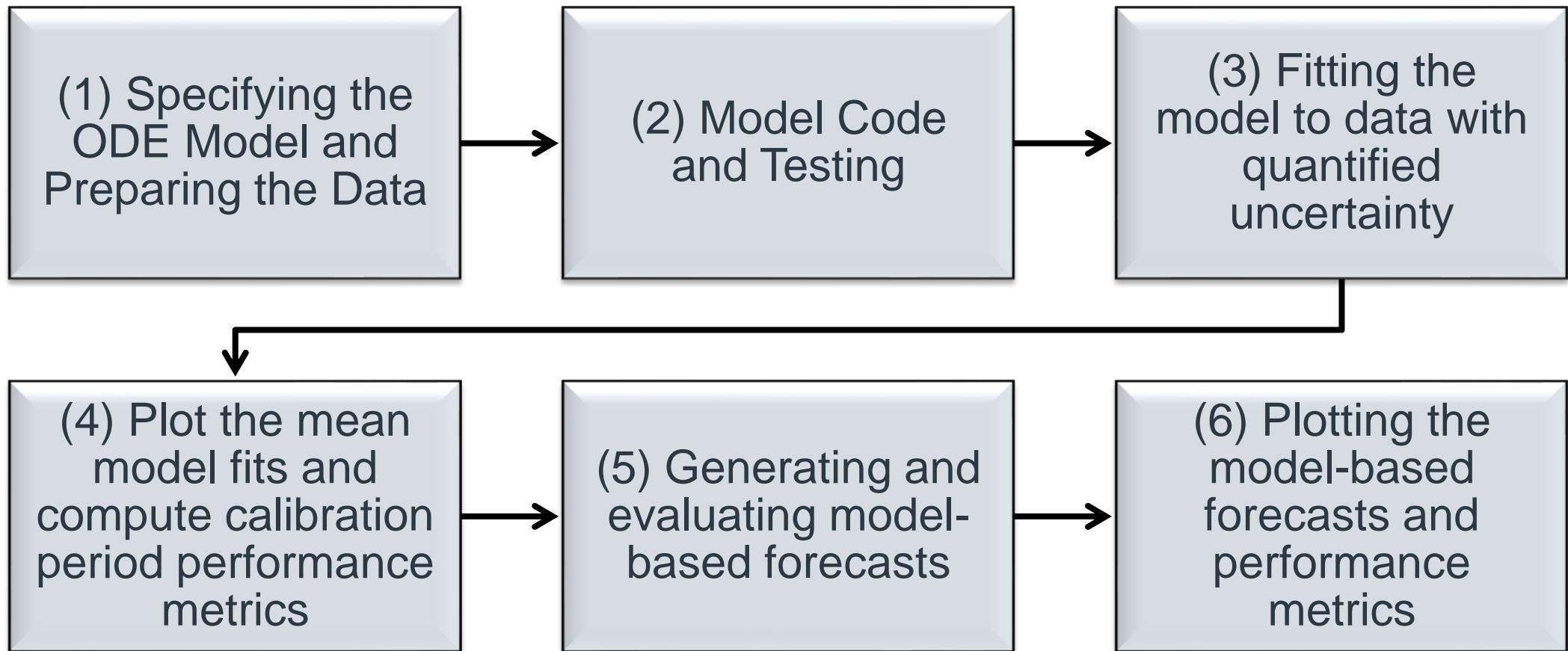


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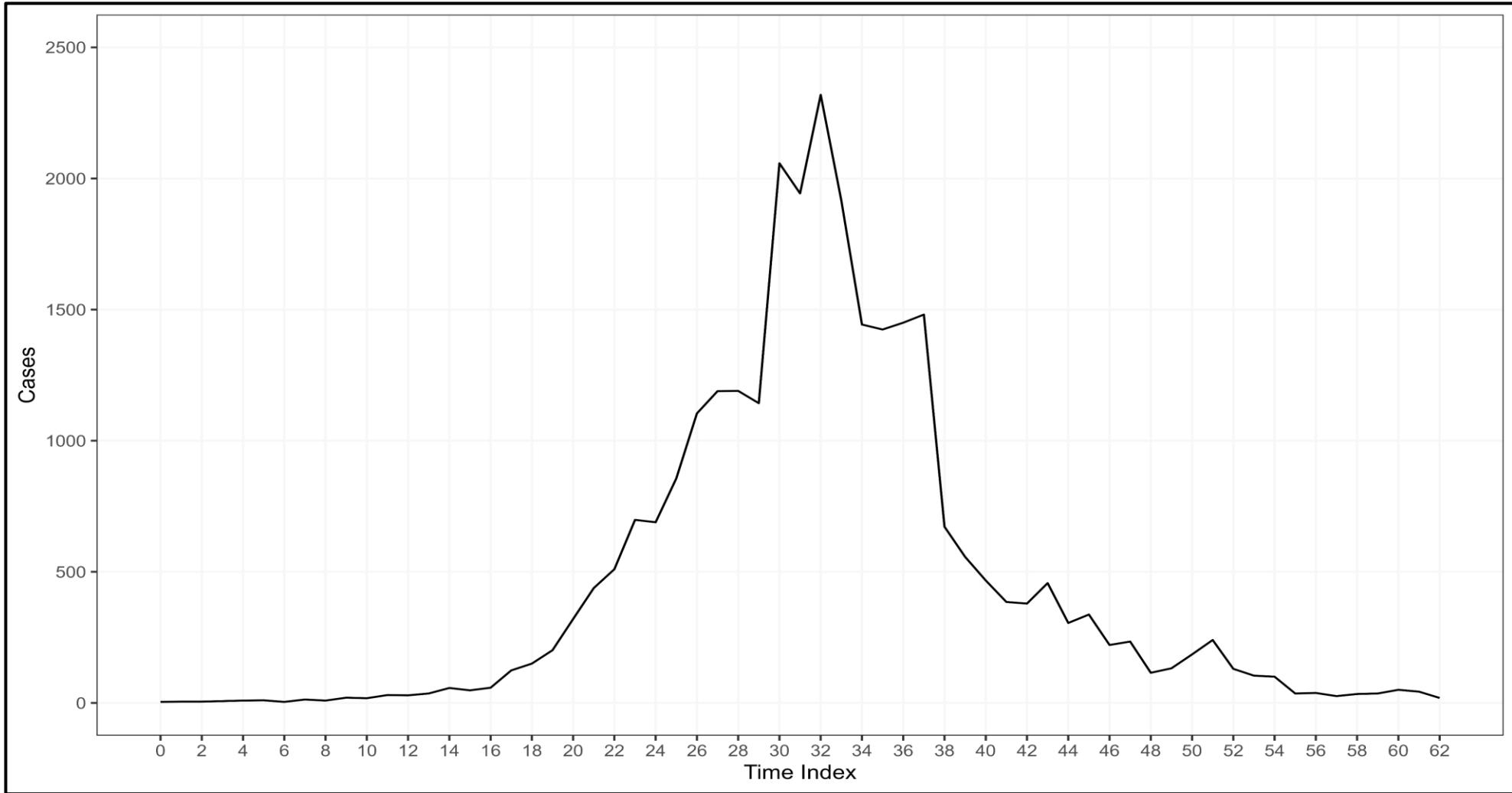
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Preparing for the Tutorial

Workflow



Tutorial #1: 1918 Influenza



Daily incident curve of the fall wave of the 1918 influenza pandemic in San Francisco.

Preparing the data

Set-Up

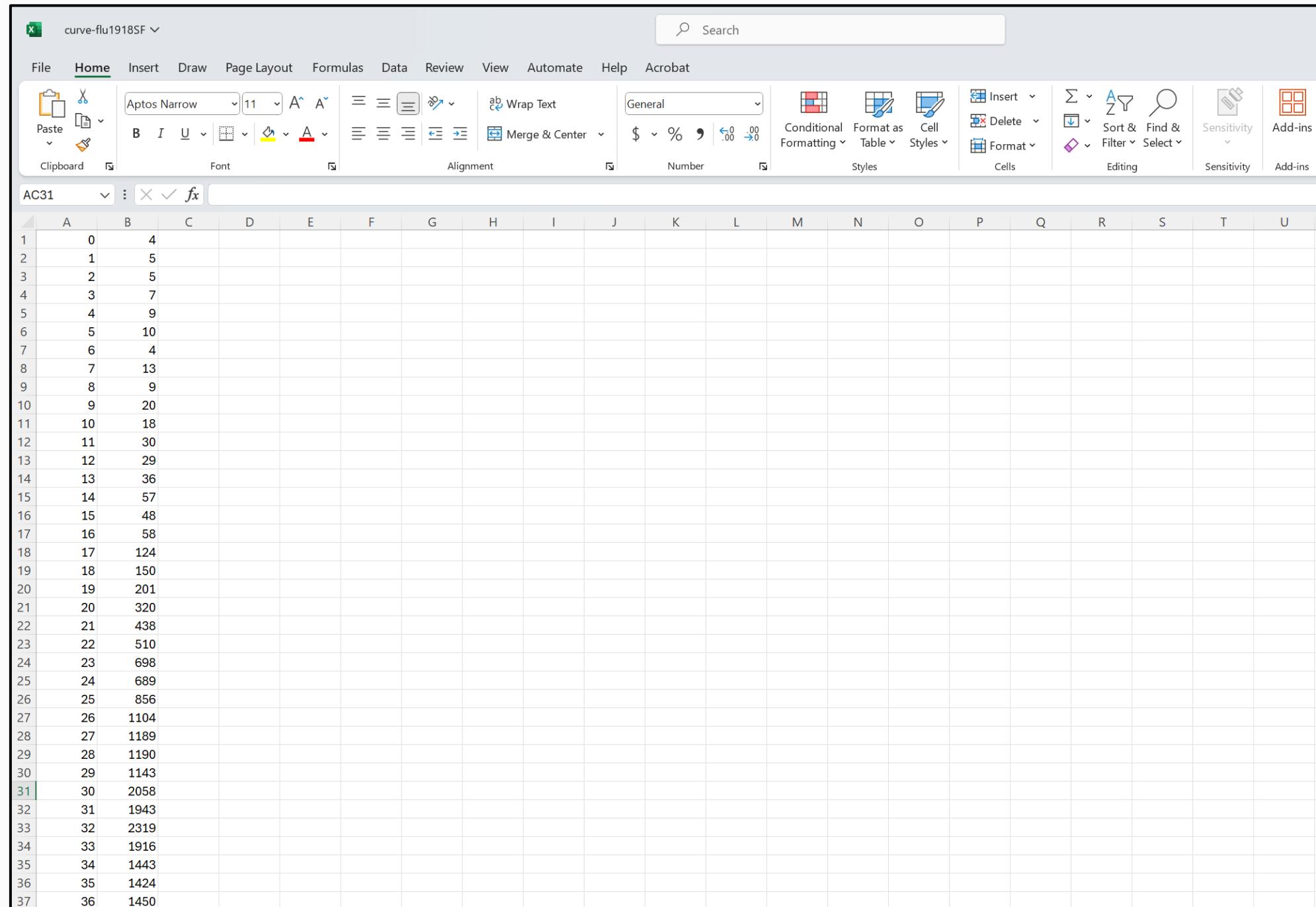
- Two folders are needed in your working directory: (1) input & (2) output
- Data goes in the input folder

File Name

- No formal file naming conventions must be followed IF working with incident data
- If working with CUMULATIVE incidence count data, the name of the time series data file must start with cumulative

File Structure

- 1st Column: Time Index (0, 1, 2...)
- 2nd Column: Temporal Incidence
- Columns should NOT have headers
- Data should be in *.txt* format



Specifying the ODE Model

Specifying the SEIR Model

```
% <=====
% < Author: Gerardo Chowell =====
% <=====

function dx=SEIR1(t,x,params0,extra0)

% params0(1) = beta, params0(2)=k,  params0(3)=gamma, params0(4)=N

dx=zeros(5,1); % define the vector of the state derivatives

dx(1,1)= -params0(1)*x(1,1).*x(3,1)./params0(4); %S
dx(2,1)= params0(1)*x(1,1).*x(3,1)/params0(4) -params0(2)*x(2,1); %E
dx(3,1)= params0(2)*x(2,1) - params0(3)*x(3,1); %I
dx(4,1)= params0(3)*x(3,1); %R
dx(5,1)= params0(2)*x(2,1); %cumulative infections
```

$$\begin{cases} \dot{S} = -\beta S(t) \frac{I(t)}{N} \\ \dot{E} = \beta S(t) \frac{I(t)}{N} - \kappa E(t) \\ \dot{I} = \kappa E(t) - \gamma I(t) \\ \dot{R} = \gamma I(t) \\ \dot{C} = \kappa E(t) \end{cases}$$

Specifying the R0 Function

- In addition to specifying the ODE model, users can choose to specify a composite function using parameters specified in the ODE file
- For this tutorial, we use the following calculation for R0:

```
function composite_val=R0s(params0)  
  
% beta(1), k(2), gamma(3), N(4)  
composite_val=params0(:,1)./params0(:,3);
```

$$R0 = \frac{\beta}{\gamma}$$

Preparing the options_fit.m file

Overview

- Prior to fitting the model to data, multiple parameters must be specified in an `options_fit.m` structured file.
 - Name of `options_fit` file can be customized.
- Required Specification Sections :
 - Dataset Properties
 - Parameter Estimation
 - ODE Model
 - Rolling Window Analysis

Tutorial: We will be using two different `options_fit.m` files for this tutorial:

- (1) `options_fit_SEIR_flu1918_dist1_1`
- (2) `options_fit_SEIR_flu1918_dist1_3`

```

% <===== Declare global variables =====>
% <===== Declare global variables =====>
% <===== Declare global variables =====>

global method1 % Parameter estimation method

% <===== Datasets properties =====>
% <===== Datasets properties =====>
% <===== Datasets properties =====>
% Located in the input folder, the time series data file is a text file with extension *.txt.
% The time series data file contains the incidence curve of the epidemic of interest.
% The first column corresponds to time index: 0,1,2, ... and the second
% column corresponds to the observed time series data.

cadfilename1='curve-flu1918SF'

caddisease='1918 Flu'; % string indicating the name of the disease related to the time series data

datatype='cases'; % string indicating the nature of the data (cases, deaths, hospitalizations, etc)

```

- (1) `cadfilename1`: The name of the data file.
- (2) `caddisease`: Name of the process of interest
- (3) `datatype`: Nature of the data

```

% ===== Parameter estimation =====
method1=1; % Type of estimation method
% Nonlinear least squares (LSQ)=0,
% MLE Poisson=1,
% MLE (Neg Binomial)=3, with VAR=mean+alpha*mean;
% MLE (Neg Binomial)=4, with VAR=mean+alpha*mean^2;
% MLE (Neg Binomial)=5, with VAR=mean+alpha*mean^d;

dist1=1; % Define dist1 which is the type of error structure. See below:

%dist1=0; % Normal distribution to model error structure (method1=0)
%dist1=1; % Poisson error structure (method1=0 OR method1=1)
%dist1=2; % Neg. binomial error structure where var = factor1*mean where
          % factor1 is empirically estimated from the time series
          % data (method1=0)
%dist1=3; % MLE (Neg Binomial) with VAR=mean+alpha*mean (method1=3)
%dist1=4; % MLE (Neg Binomial) with VAR=mean+alpha*mean^2 (method1=4)
%dist1=5; % MLE (Neg Binomial)with VAR=mean+alpha*mean^d (method1=5)

switch method1
  case 1
    dist1=1;
  case 3
    dist1=3;
  case 4
    dist1=4;
  case 5
    dist1=5;
end

numstartpoints=20; % Number of initial guesses for optimization procedure using MultiStart
B=300; % number of bootstrap realizations to characterize parameter uncertainty

```

(1) method1 : The type of estimation method.

- Five options available: NLSQ, MLE Poisson, and three MLE Neg. Binomial options
- The estimation method option should match the appropriate error structure.

(2) dist1: Error structure

- Six options available: Normal, Poisson, and four Neg. Binomial options

(3) numstartpoints: Number of initial guesses for optimization procedure

(4) B: Number of bootstrap realizations

*Tutorial: As we are working with smaller case counts, we will stick with Poisson and Negative Binomial error structures.

Specifying the ODE Model – options_fit.m

```
% <===== ODE model =====>
% <===== ODE model =====>
% <===== ODE model =====>

model.fc=@SEIR1; % name of the model function
model.name='SEIR model'; % string indicating the name of the ODE model

params.label={'\beta','\kappa','\gamma','N'}; % list of symbols to refer to the model parameters
params.LB=[0.01 0.01 0.01 20]; % lower bound values of the parameter estimates
params.UB=[10 2 2 1000000]; % upper bound values of the parameter estimates
params.initial=[0.6 1/1.9 1/4.1 550000]; % initial parameter values/guesses
params.fixed=[0 1 1 1]; % Boolean vector to indicate any parameters that should remain fixed (1) to initial values indicated in params.initial. Otherwise the parameter is estimated.
params.fixI0=1; % Boolean variable indicating if the initial value of the fitting variable is fixed according to the first observation in the time series (1). Otherwise, it is estimated.
params.composite=@R0s; % Estimate a composite function of the individual model parameter estimates otherwise it is left empty.
params.composite_name='R_0'; % Name of the composite parameter
params.extra0=[];

vars.label={'S','E','I','R','C'}; % list of symbols to refer to the variables included in the model
vars.initial=[params.initial(4)-4 0 4 0 4]; % vector of initial conditions for the model variables
vars.fit_index=5; % index of the model's variable that will be fit to the observed time series data
vars.fit_diff=1; % boolean variable to indicate if the derivative of model's fitting variable should be fit to data.
```

```
% <===== Parameters of the rolling window analysis =====>
% <===== Parameters of the rolling window analysis =====>
% <===== Parameters of the rolling window analysis =====>

windowsize1=17; % moving window size

tstart1=1; % time point for the start of rolling window analysis

tend1=1; %time point for the end of the rolling window analysis

printscreen1=1;
```

- (1) windowsize1: The size of the moving window or calibration period
- (2) tstart1: Start of the rolling window analysis
- (3) tend1: End of the rolling window analysis
- (4) printscreen1: Show the plots at the conclusion of running code

Rolling Window Analysis

- A rolling window analysis can be useful to assess the stability of the model parameters and forecasts over
 - Controls the data used to calibration the model (i.e., data that goes into the model)

Example: tstart1 = 1, tend1 = 2, windowsize1 = 5

Time	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Cases	1	2	5	8	9	1	2	1	1	5	3	6	9	4	8	0

Rolling Window #1

Rolling Window #2

Given $tstart1 = 3$, $tend1 = 3$, and $windowSize1 = 5$, what is the start and end time index of the rolling window analysis?

0

(A) 3, 3

0%

(B) 1, 2

0%

(C) 1, 3

0%

(D) 4, 5

0%

(E) I'm not sure.

0%

Time	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Cases	1	2	5	8	9	1	2	1	1	5	3	6	9	4	8	0

Generating preliminary model solutions

plotODEModel()

Overview

- It's often helpful to check that the user has correctly specified the model by checking that the model's solutions for the parameter ranges specified by the user correspond to a broad range of expected solutions

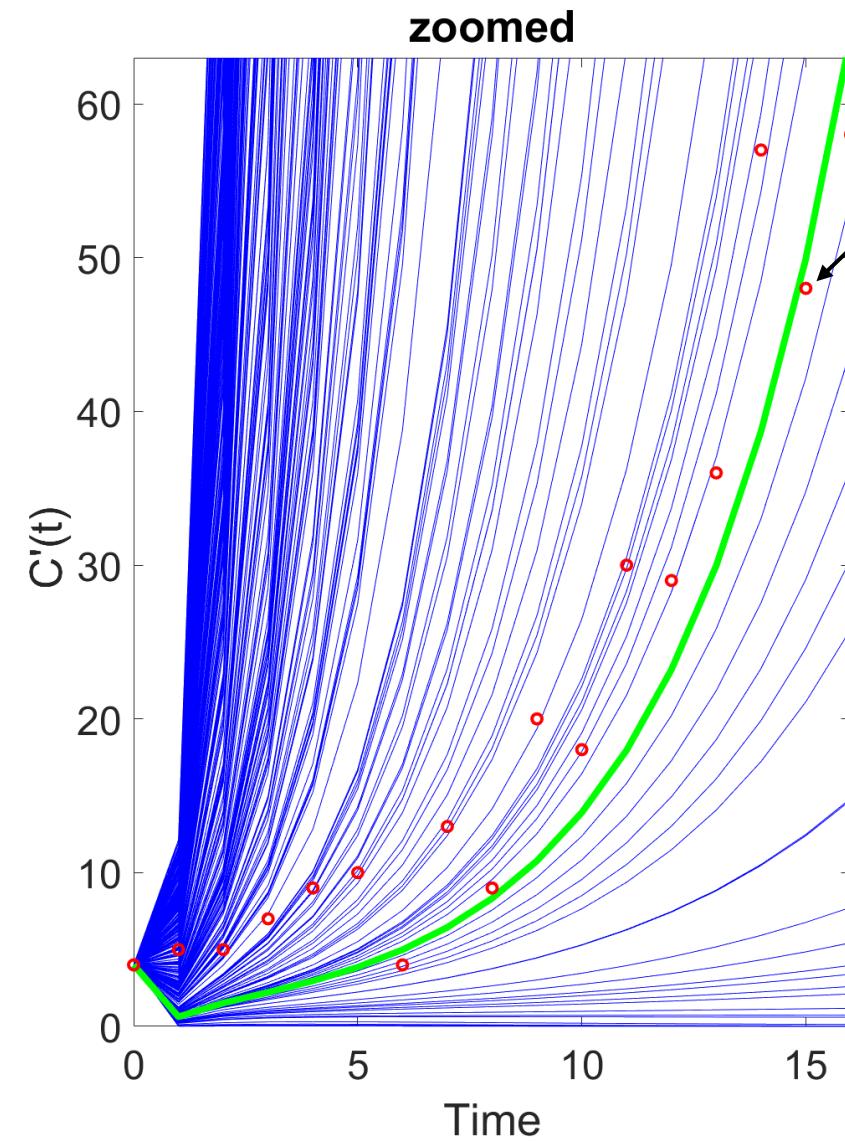
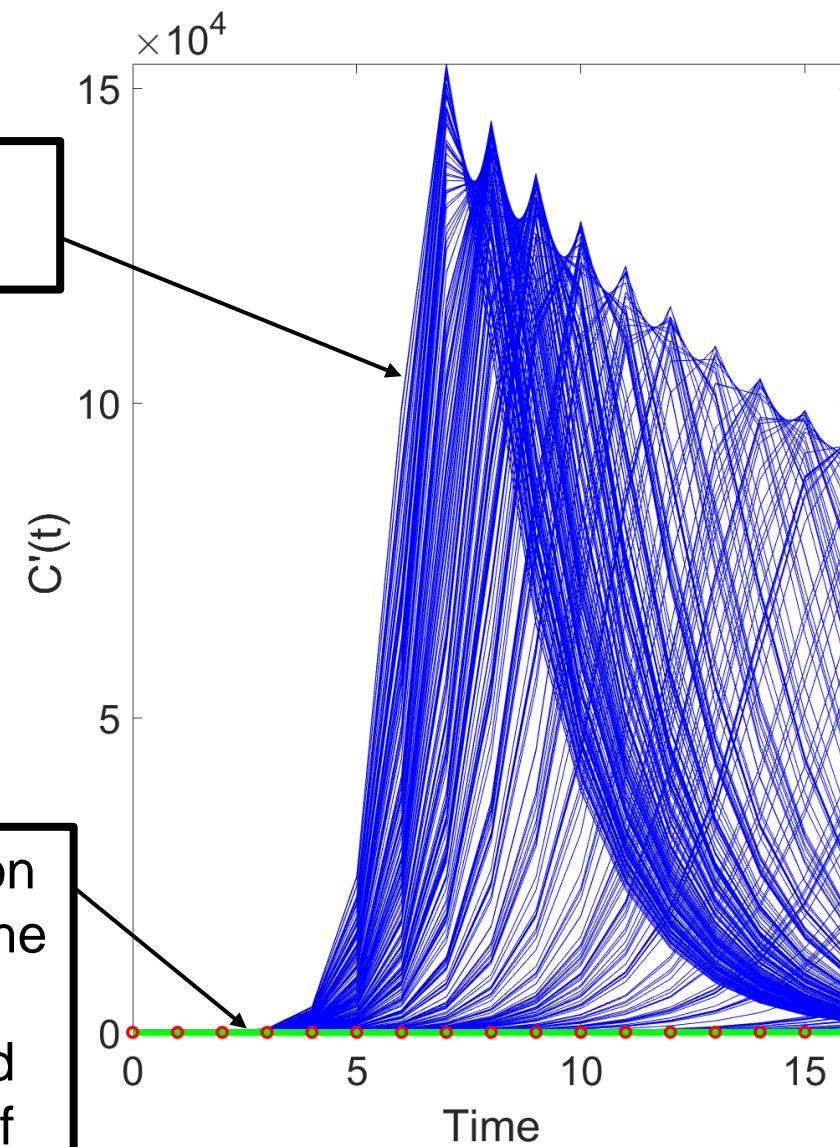
```
plotODEModel (@optionsFitFileName)
```

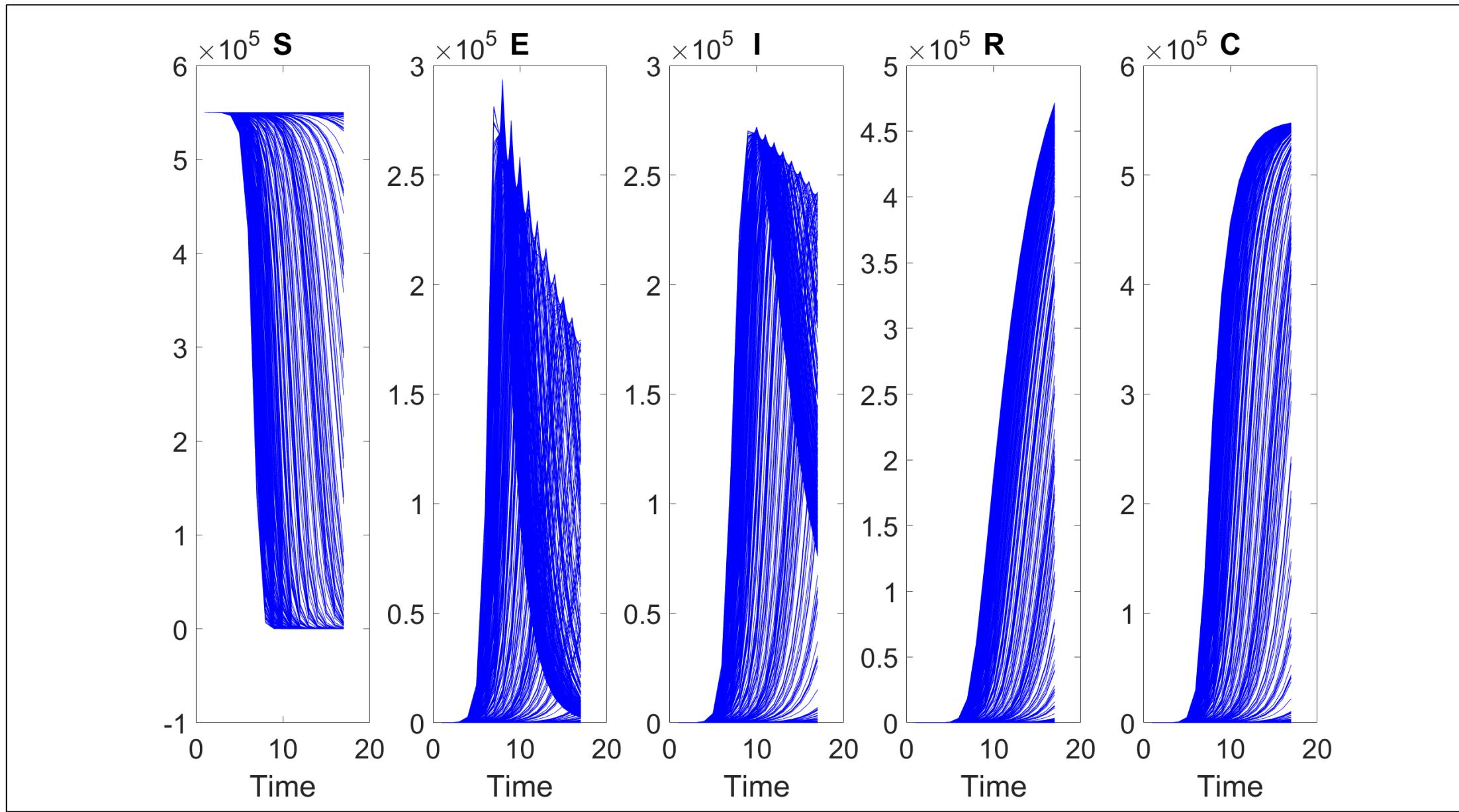
- Produces plots showing model solutions of state variables by generating a random sample of parameter sets from the specified parameter ranges and time-period

Tutorial Code Call

```
plotODEModel (@options_fit_SEIR_flu1918_dist1_1)
```

Time-series
data





Fitting, plotting, and evaluating the model with quantified uncertainty

Poisson and Neg. Binomial Error Structures

Step One: Fitting the Model to Data

- Prior to obtaining model fit files and plotting the model fit, we first must fit the model to data with quantified uncertainty using the following code call:

```
Run_Fit_ODEModel (@OptionsFitFileName, tstart1, tend1, windowsize1)
```

- `tstart1`, `tend1`, and `windowsize1` correspond to the values entered in the rolling window analysis section of the `options_fit.m` file.

Tutorial Code: (1) Poisson & (2) Negative Binomial

```
(1) Run_Fit_ODEModel (@options_fit_SEIR_flu1918_dist1_1, 1, 1, 17)  
(2) Run_Fit_ODEModel (@options_fit_SEIR_flu1918_dist1_3, 1, 1, 17)
```

Step Two: Plotting the model fit

- After obtaining the model fits, we can obtain information related to: (1) model fit, (2) model parameter estimates, (3) Monte Carlo standard errors, (4) AICc values, (5) calibration performance metrics, & (6) composite parameter information for the specified model and data using the following call (.csv files in output)

```
plotFit_ODEModel (@OptionsFitFileName, tstart1, tend1, windowsize1)
```

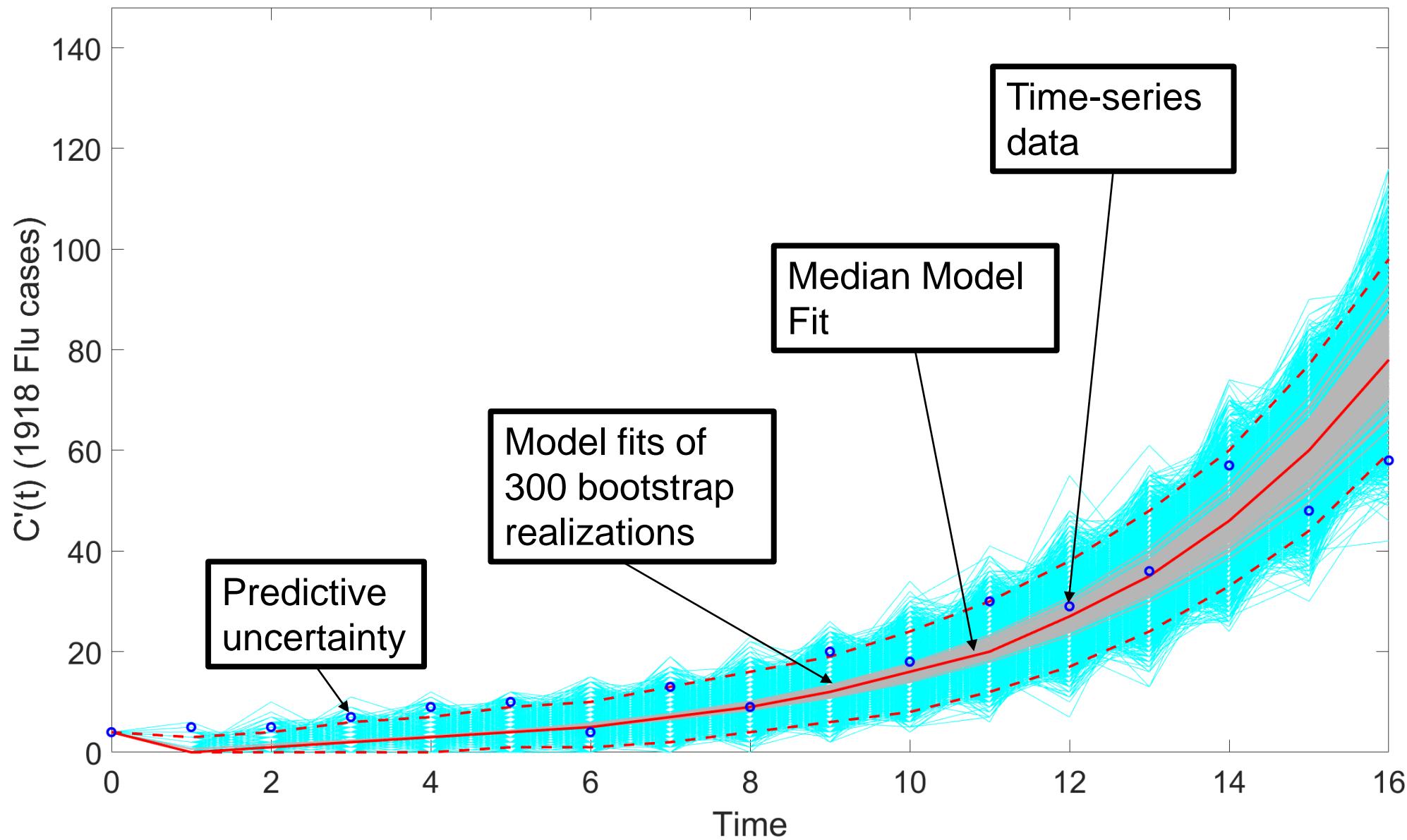
- `tstart1`, `tend1`, and `windowsize1` correspond to the values entered in the rolling window analysis section of the `options_fit.m` file.

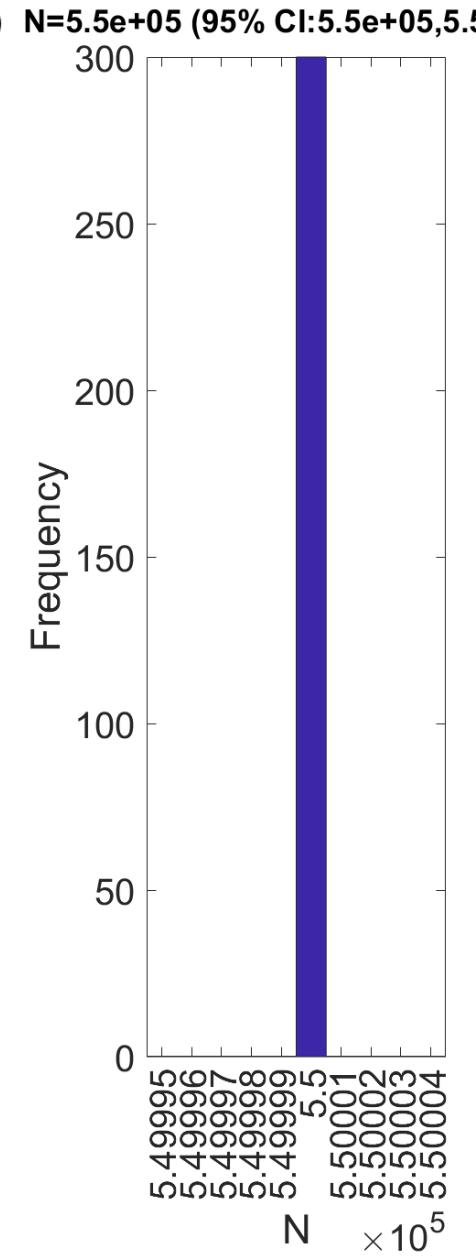
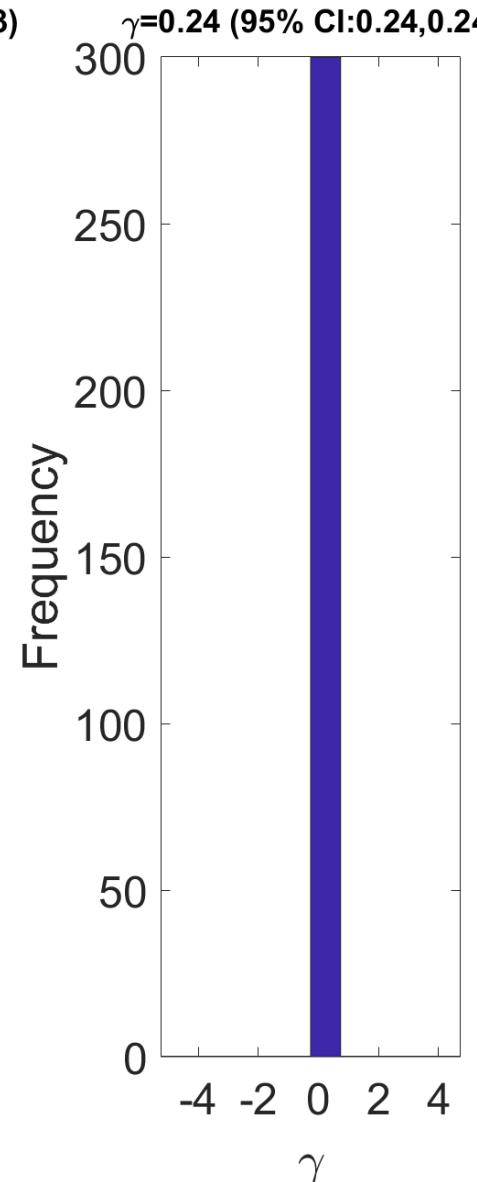
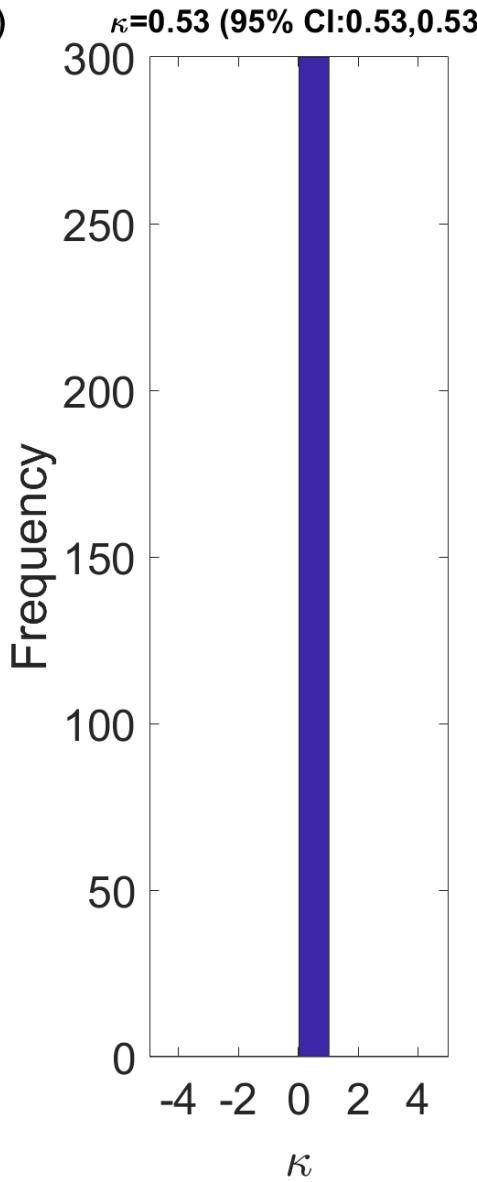
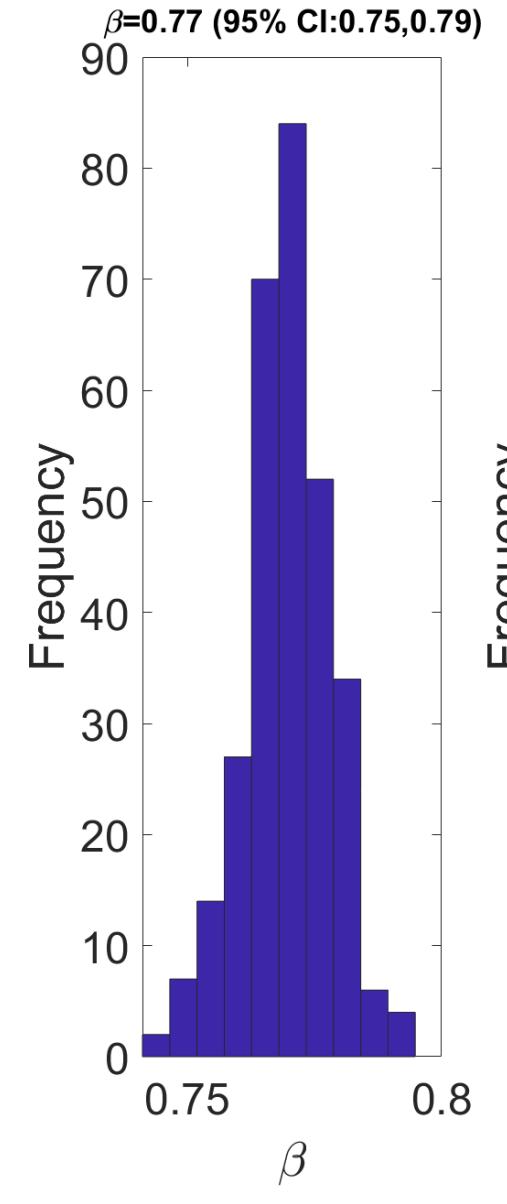
Tutorial Code Call: (1) Poisson & (2) Negative Binomial

```
(1) plotFit_ODEModel (@options_fit_SEIR_flu1918_dist1_1, 1, 1, 17)  
(2) plotFit_ODEModel (@options_fit_SEIR_flu1918_dist1_3, 1, 1, 17)
```

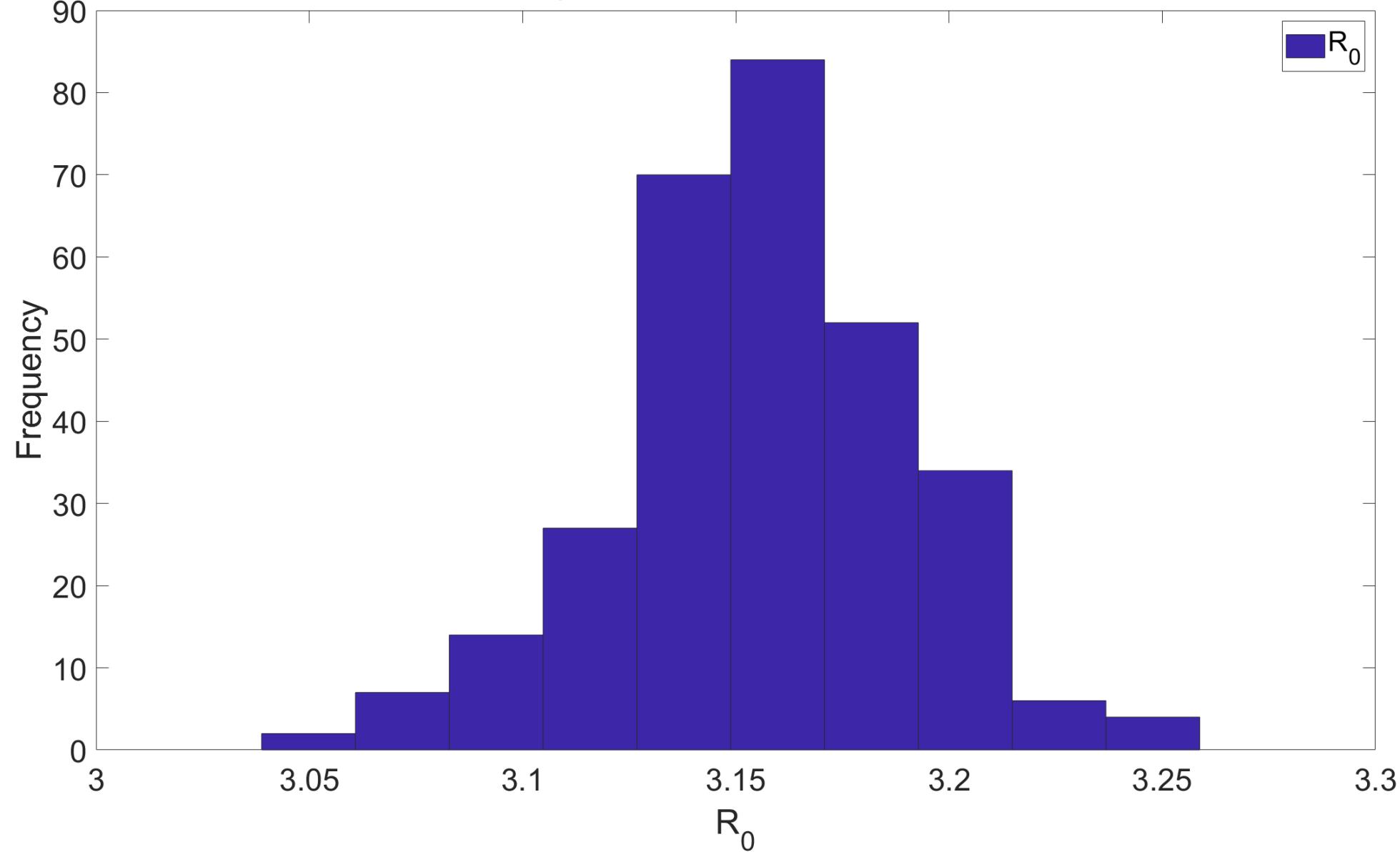
Poisson Output <dist1 = 1>

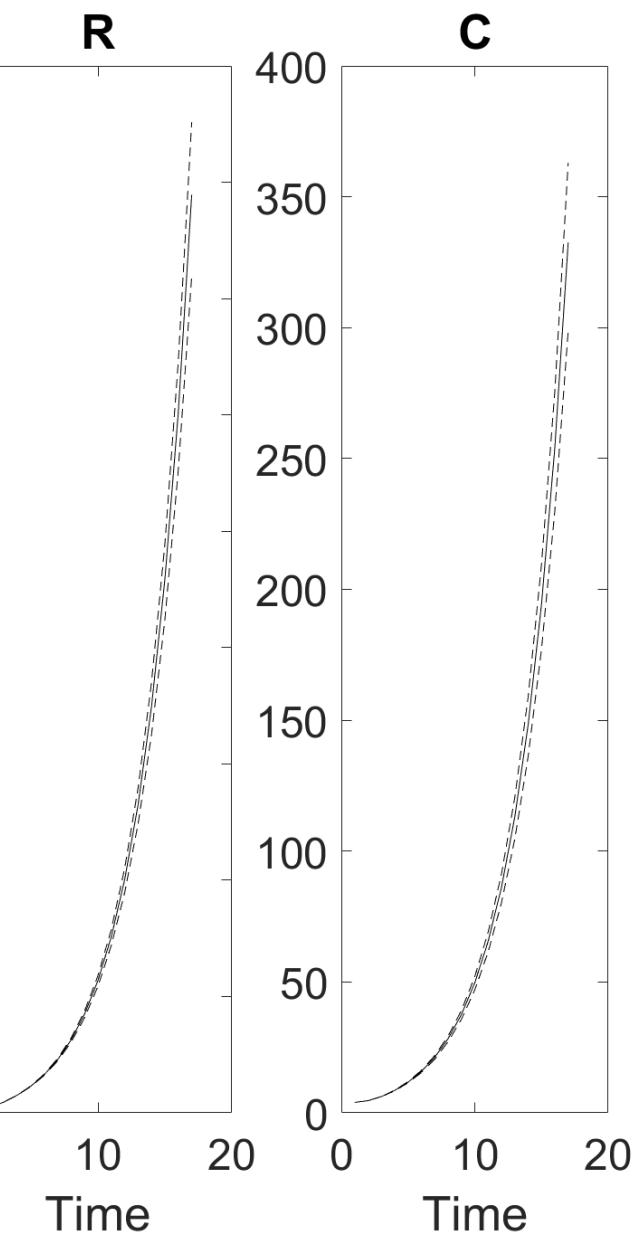
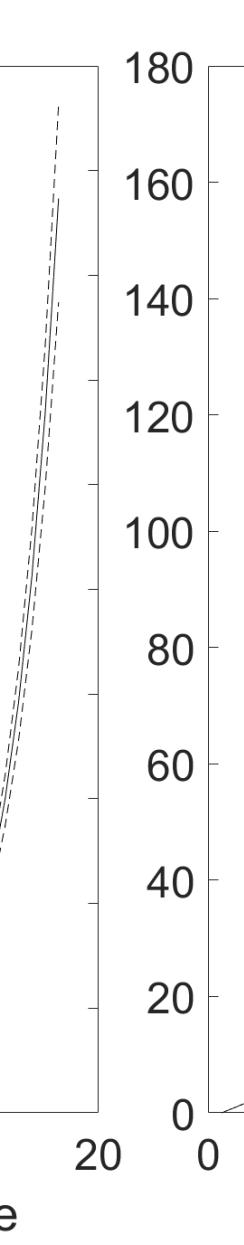
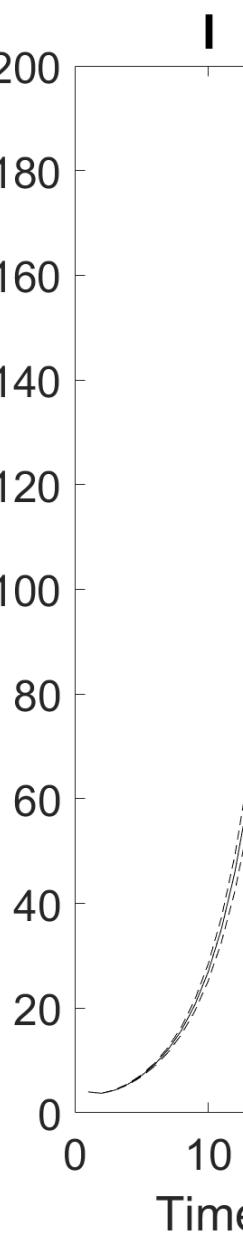
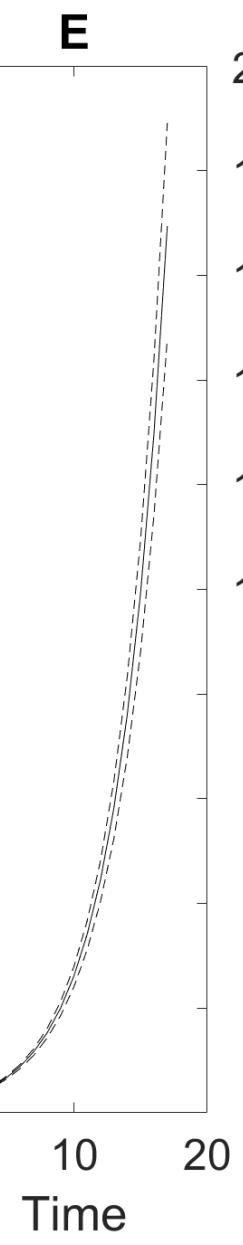
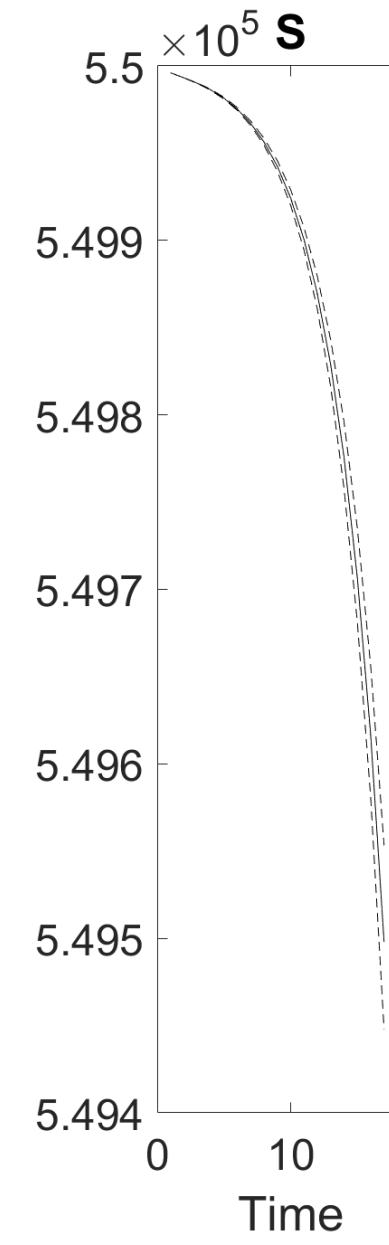
SEIR model





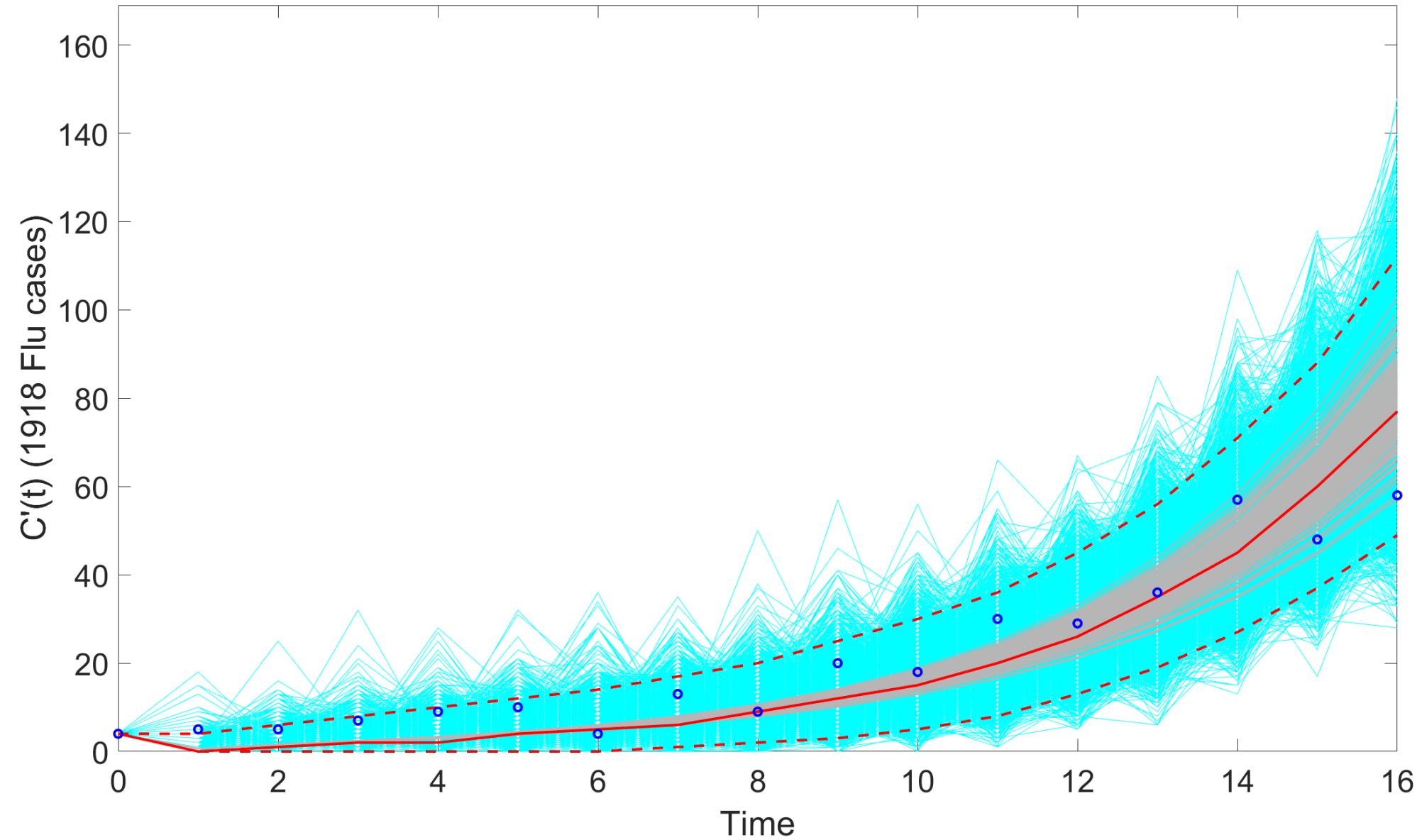
$$R_0=3.16 \text{ (95%CI:3.08,3.22)}$$

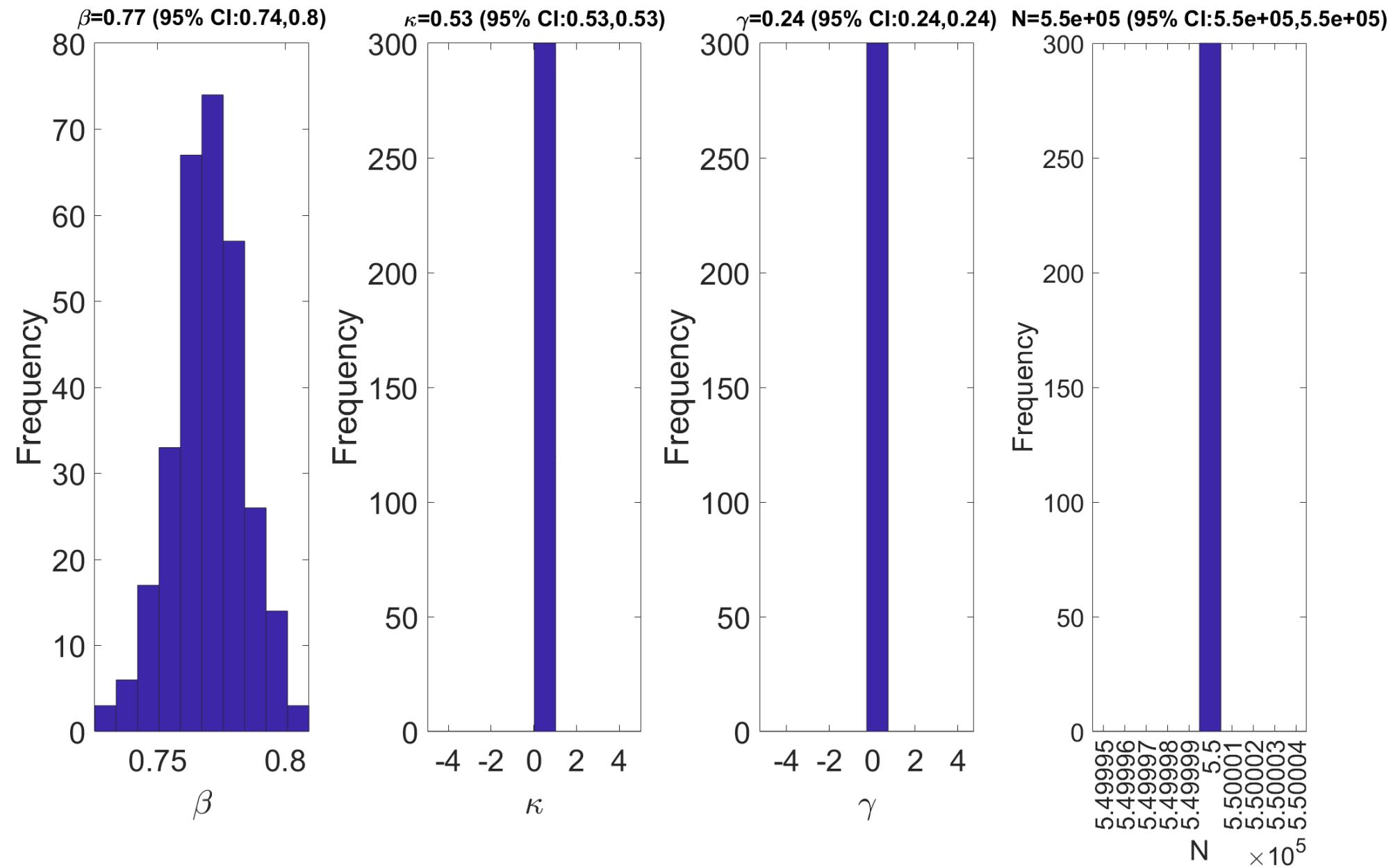


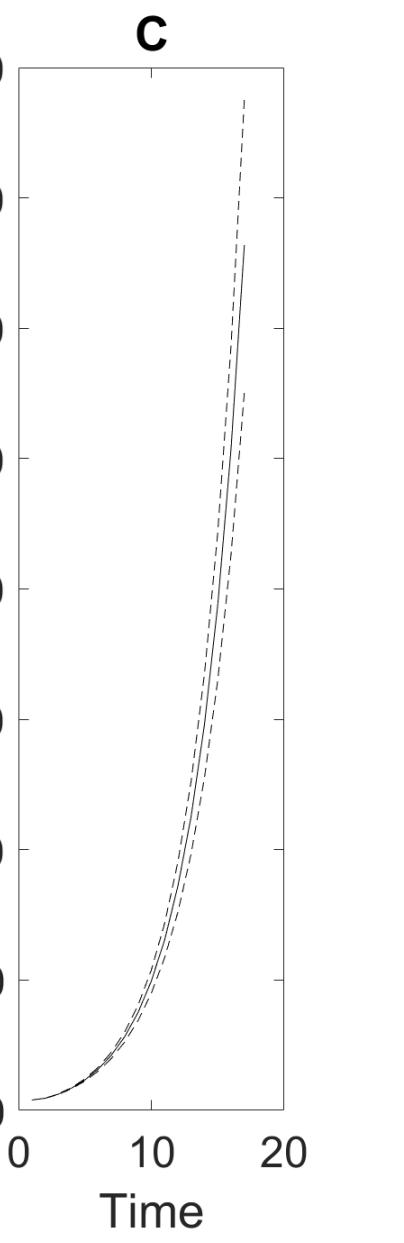
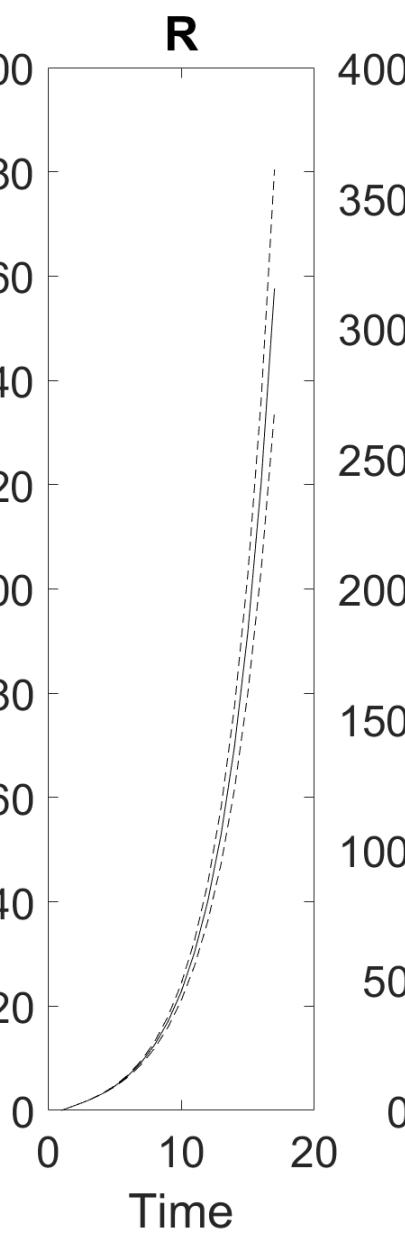
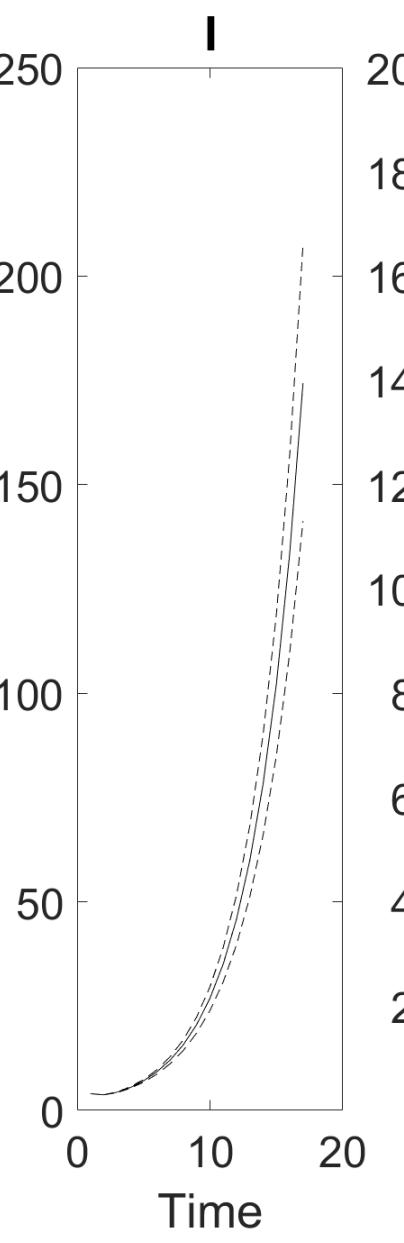
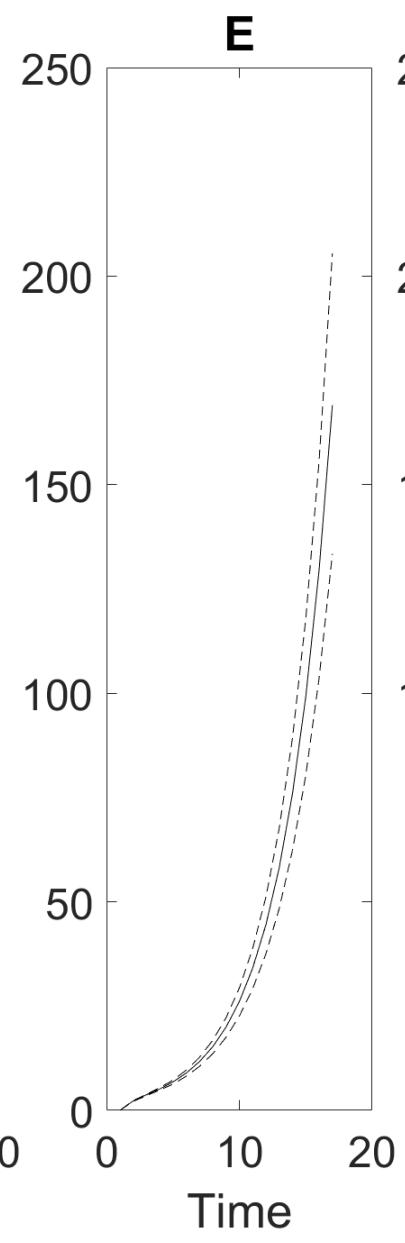
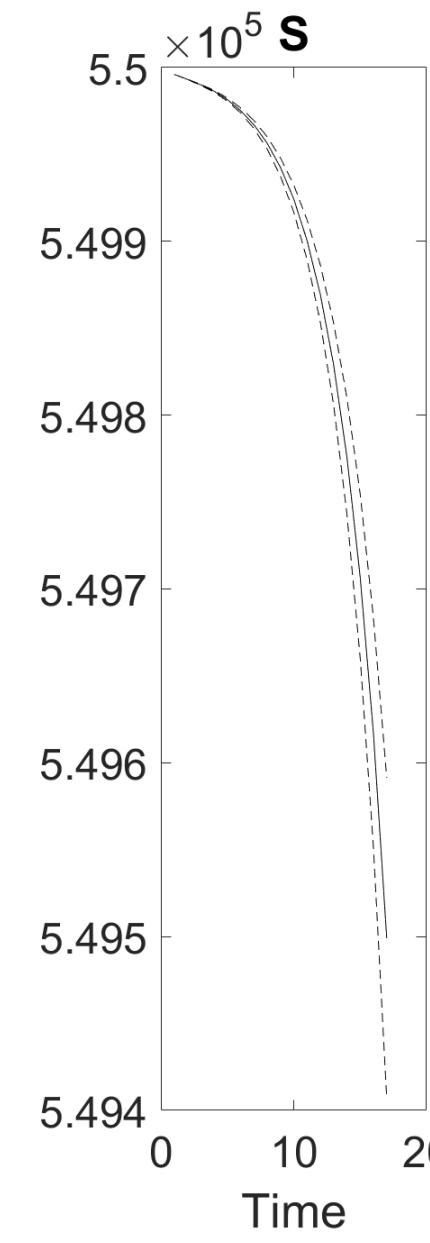


Neg. Binomial Output <dist1 = 3>

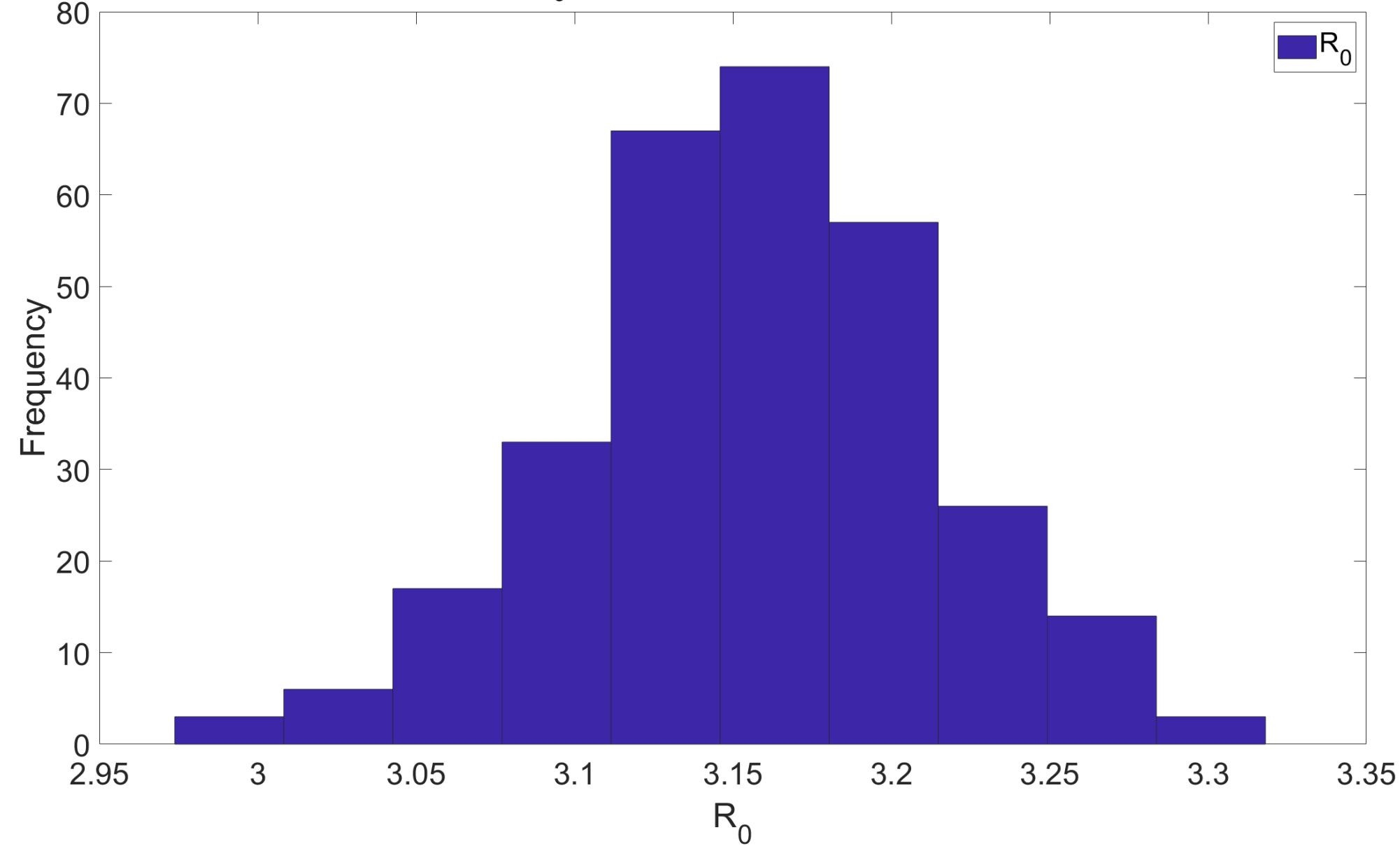
SEIR model





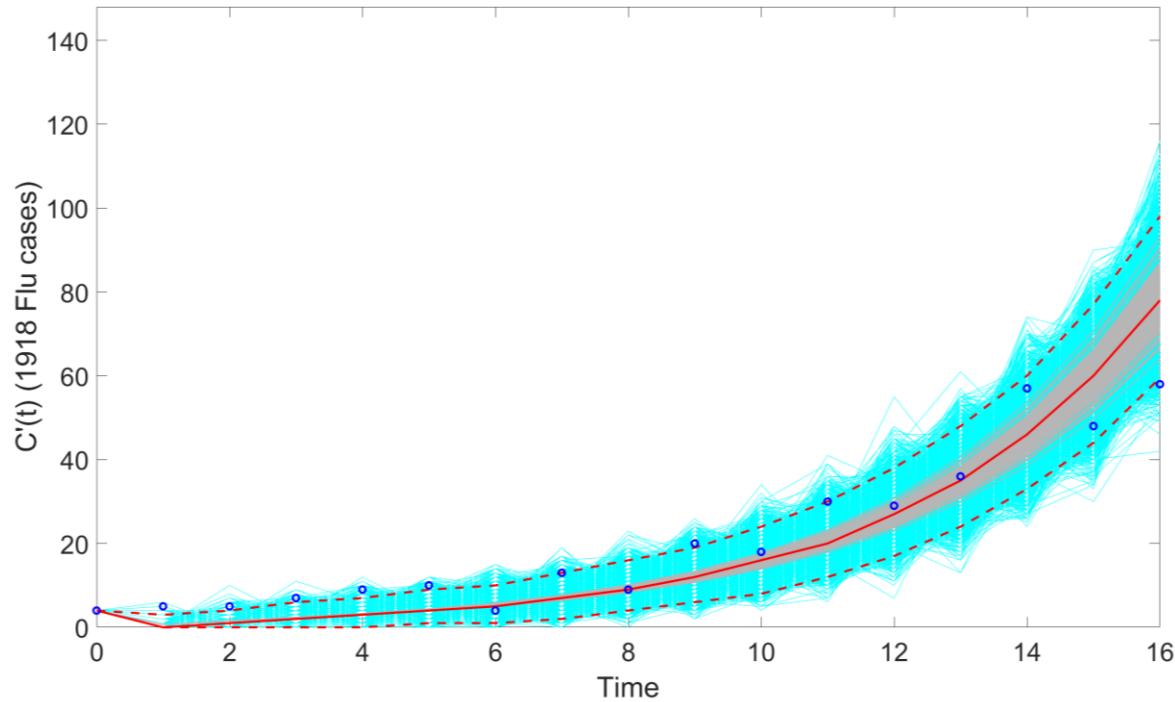


$$R_0=3.15 \text{ (95%CI:3.02,3.27)}$$

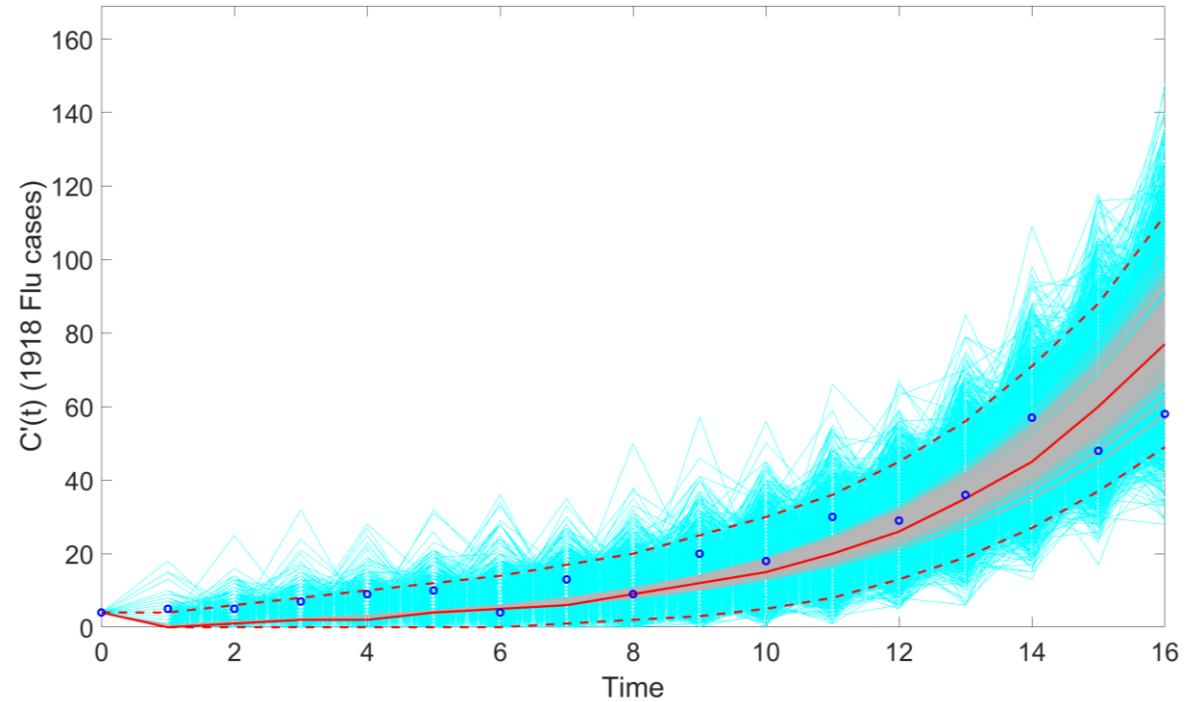


Model Fit Comparison

SEIR model

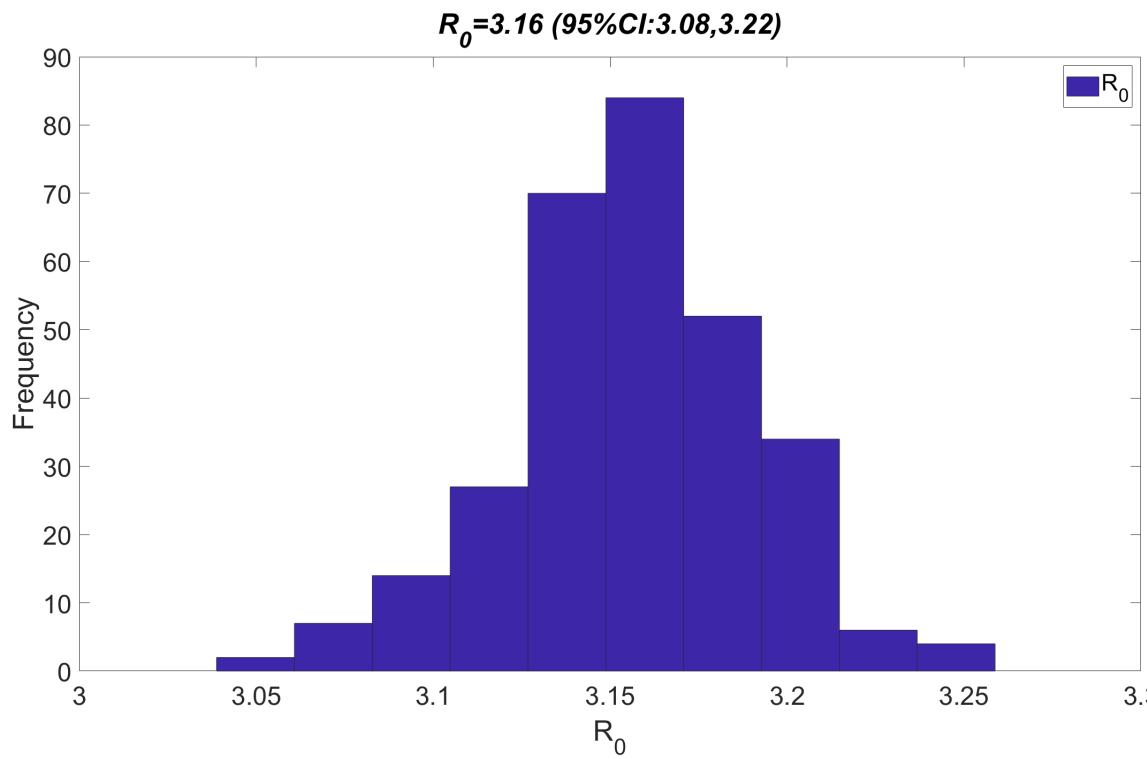


SEIR model

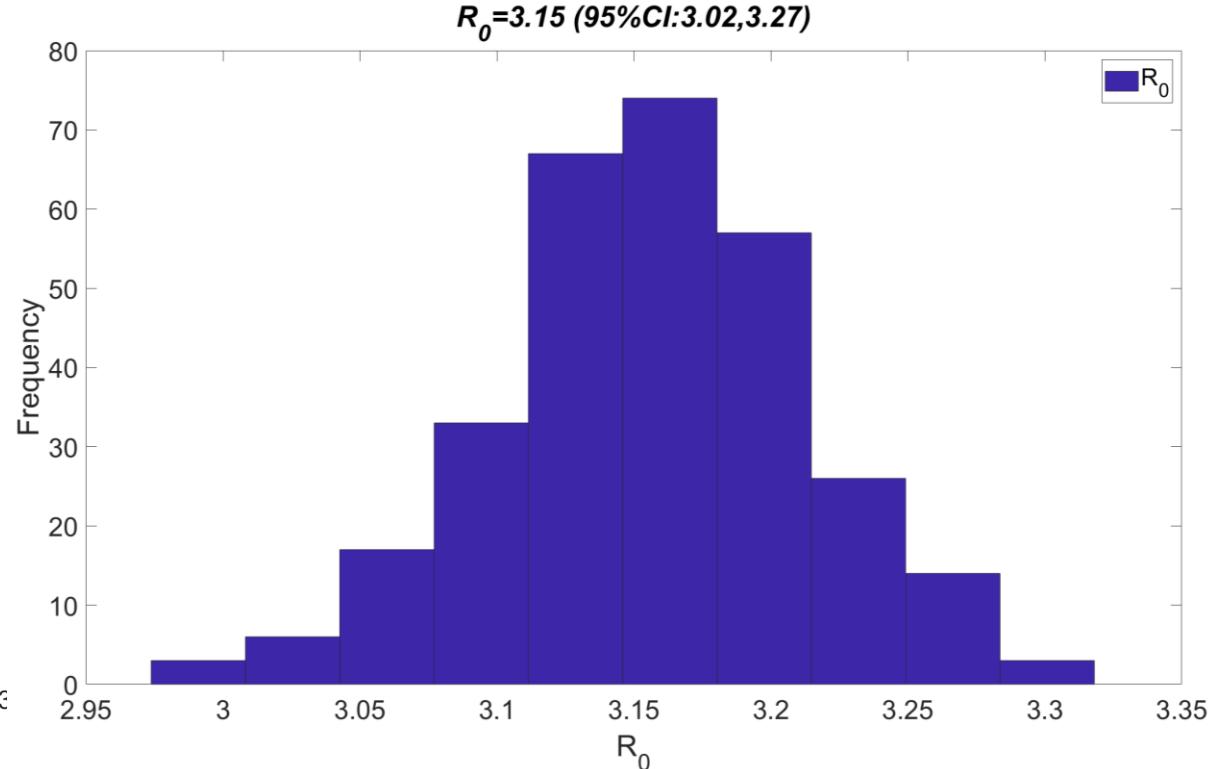


Poisson

Neg. Binomial



Poisson



Neg. Binomial

Model	MAE	MSE	Coverage 95% PI	WIS
SEIR model with Poisson error structure ($\langle \text{dist1} \rangle = 1$)	5.72	58.59	58.82	3.87
SEIR model with negative binomial error structure ($\langle \text{dist1} \rangle = 3$)	5.73	58.21	94.12	3.67

* Obtained from .csv performance-calibration... files

Generating, plotting and assessing model-based forecasts

Neg. Binomial Error Structure & Exponential Model

Step One: Preparing the Code

```
% <===== Forecasting parameters =====>
% <===== Forecasting parameters =====>
% <===== Forecasting parameters =====>

getperformance=1; % flag or indicator variable (1/0) to calculate forecasting performance or not

forecastingperiod=10; % forecast horizon (number of time units ahead)
```

- (1) `getperformance`: Indicator for calculating forecast performance metrics.
 - If the forecasting period extends past the available data, `getperformance` must be marked zero, or an error will occur.
- (2) `forecastingperiod`: The forecasting horizon (i.e., how many time points ahead the toolbox should predict)

File Name: options_forecast_SEIR_flu1918_dist1_3

Step Two: Generating Forecasts

- Prior to obtaining model fits, forecasts, and associated evaluation criteria we must generate forecasts using the following code call:

```
Run_Forecasting_ODEModels(@OptionsForecastFileName,tstart1,tend1  
                           ,windowsize1, forecastingperiod)
```

- tstart1, tend1, windowsize1, and forecastingperiod correspond to the values entered in the rolling window analysis section of the options_forecast.m file.

Tutorial Code: (1) SEIR Negative Binomial

```
(1) Run_Forecasting_ODEModel (@options_forecast_SEIR_flu1918_dist1_3,  
                               1, 1, 17,10)
```

Step Three: Plotting Forecasts

- After generating the model forecasts, we can obtain information related to: (1) forecasts, (2) model parameter estimates, (3) Monte Carlo standard errors, (4) AICc values, (5) calibration performance metrics, (6) forecast performance metrics, & (7) composite parameter information for the specified model and data using the following call (.csv files in output)

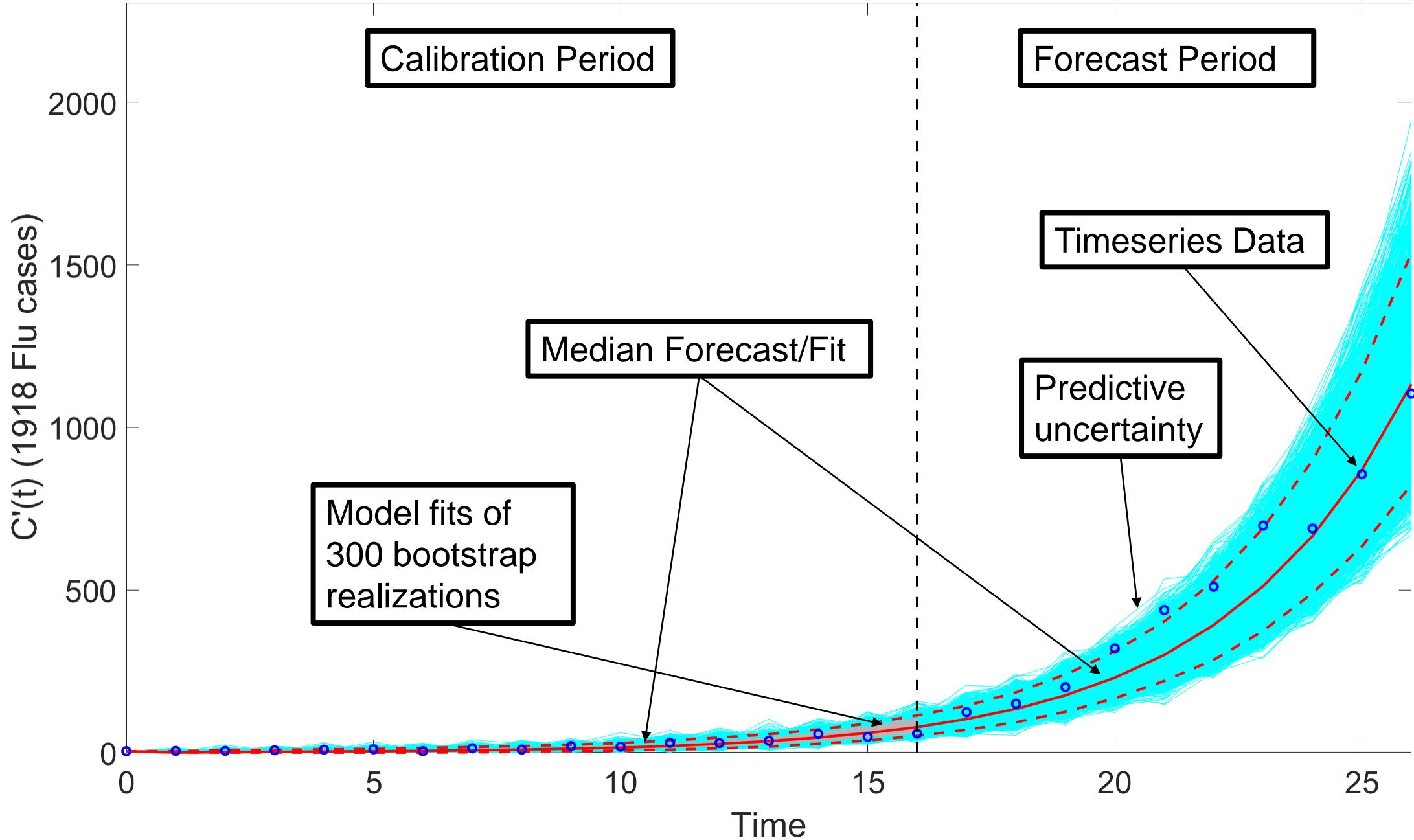
```
plotForecast_ODEModel (@OptionsForecastFileName, tstart1, tend1, windowSize1, forecastingPeriod)
```

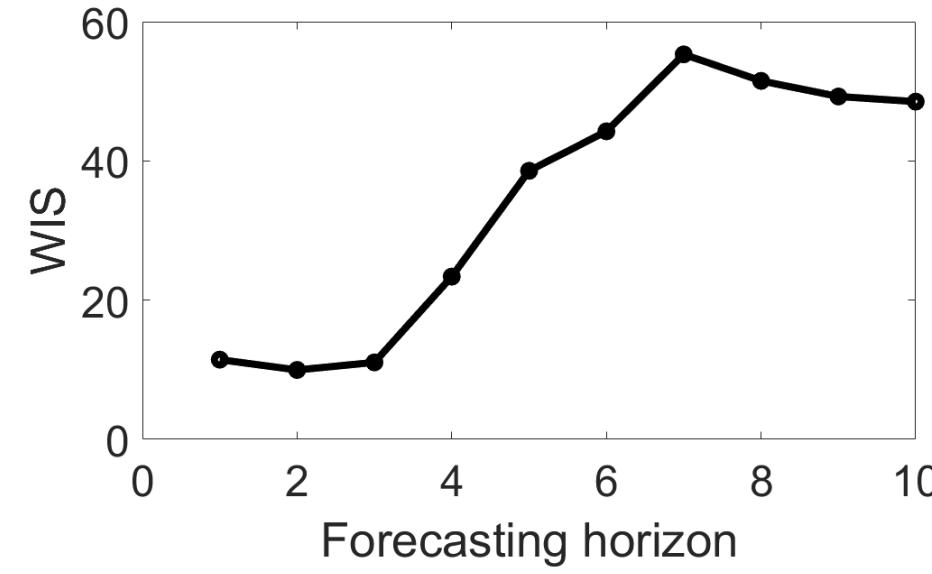
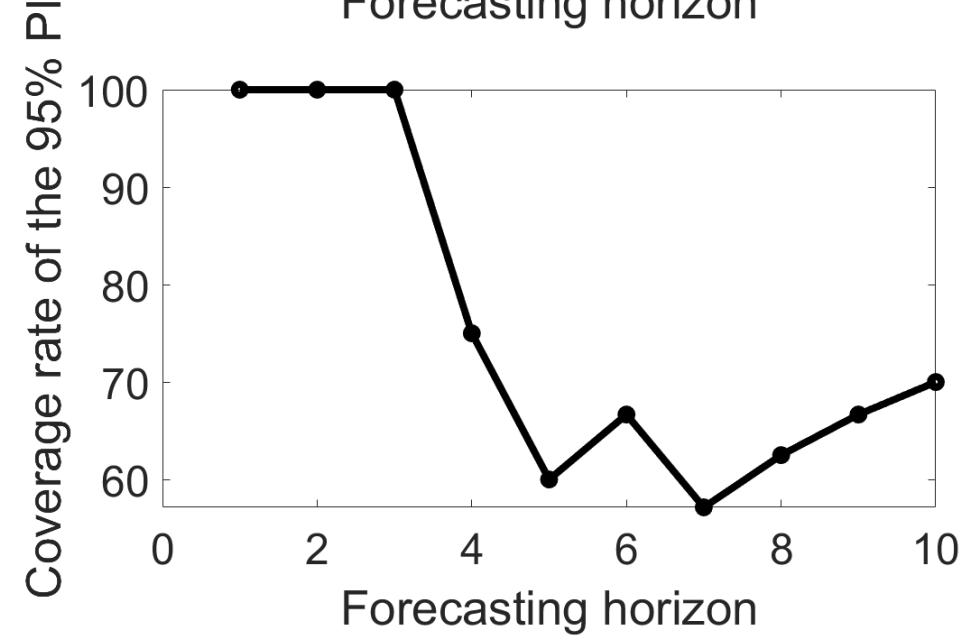
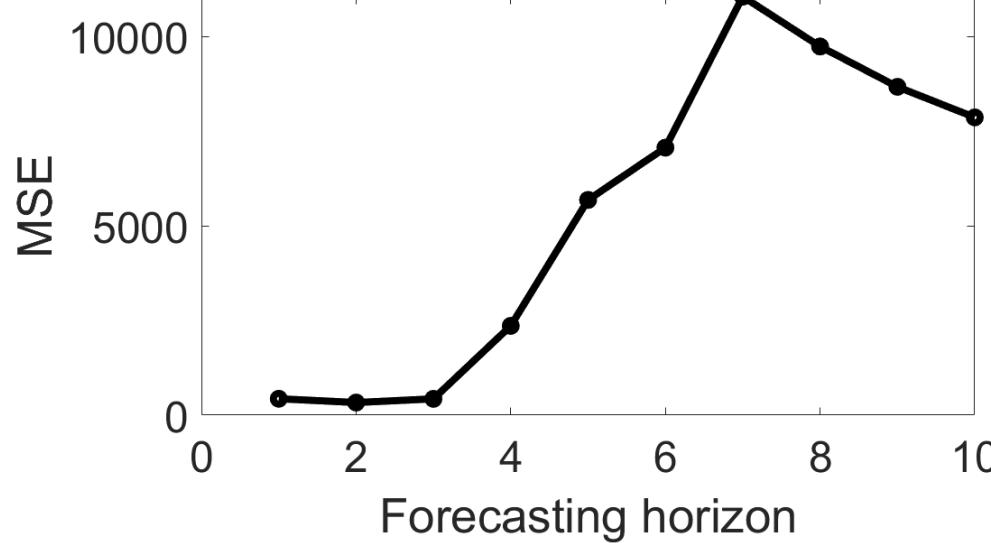
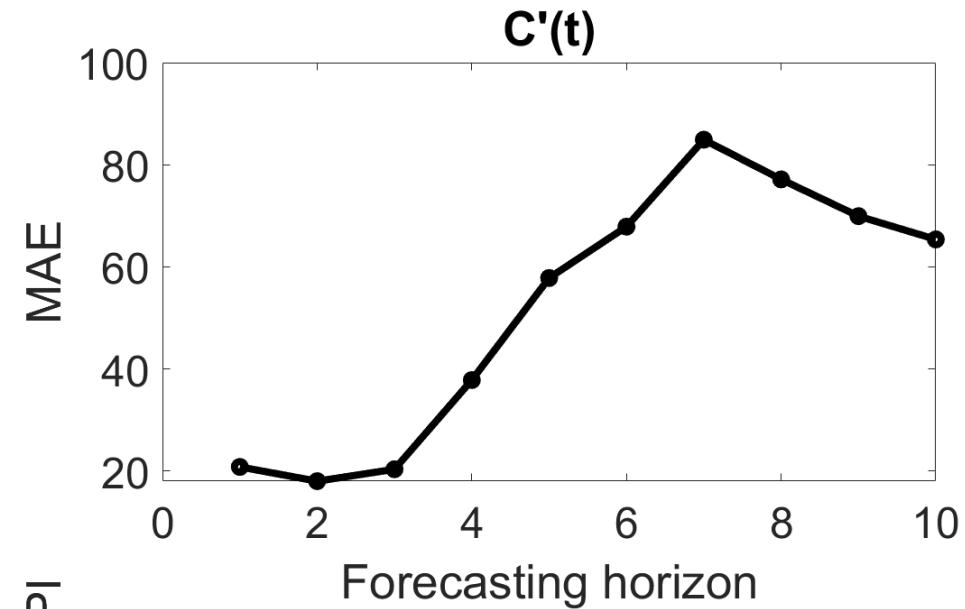
- `tstart1`, `tend1`, `windowSize1`, and `forecastingPeriod` correspond to the values entered in the rolling window analysis section of the `options_forecast.m` file.

Tutorial Code: (1) SEIR Negative Binomial

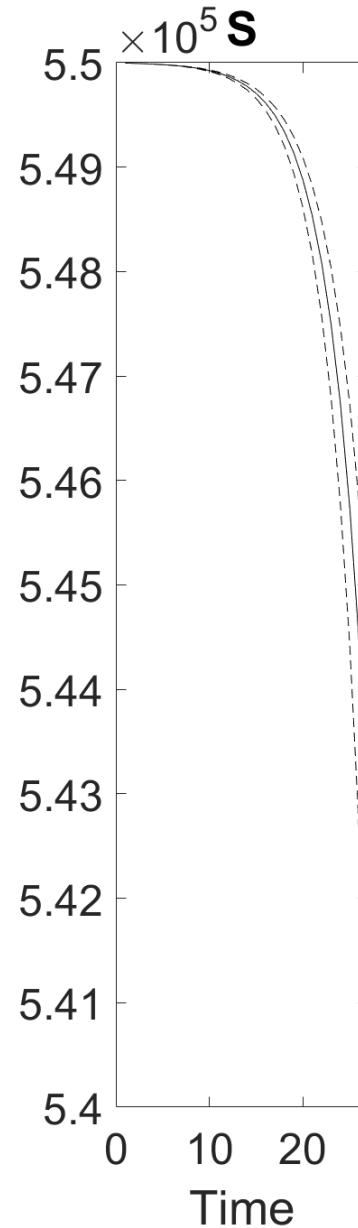
```
(1) plotForecast_ODEModel (@options_forecast_SEIR_f1918_dist1_3, 1, 1,  
17, 10)
```

SEIR model

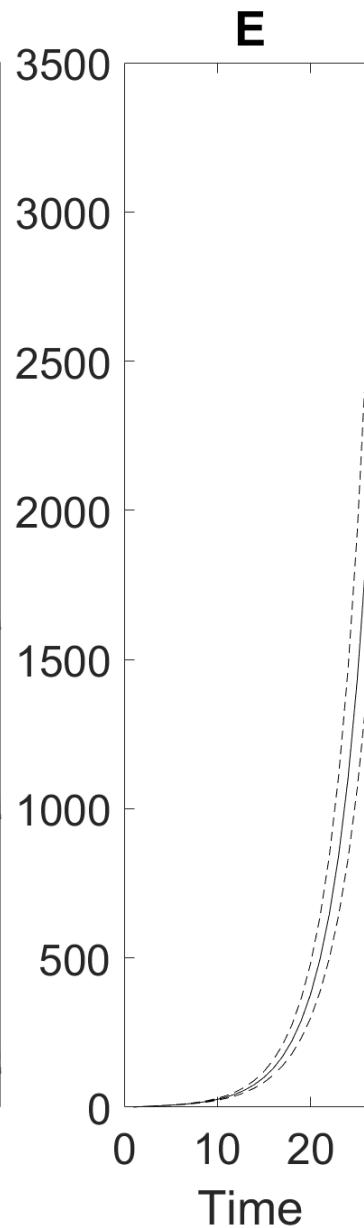




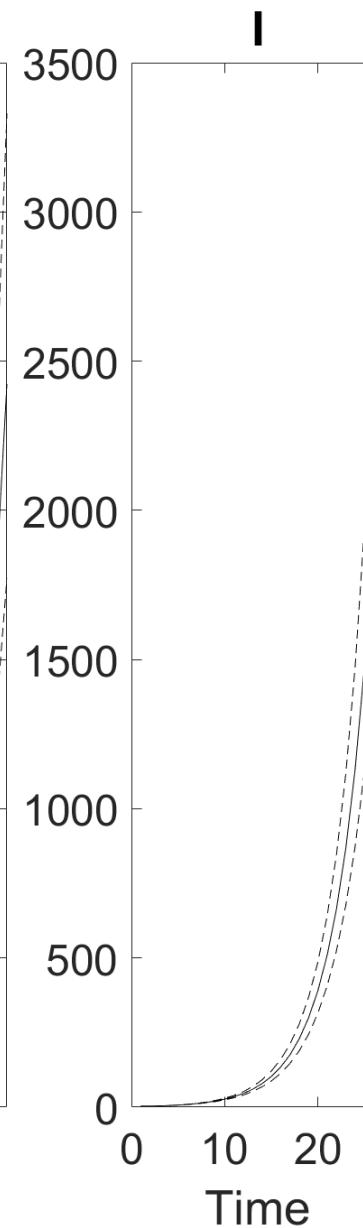
$\times 10^5$ S



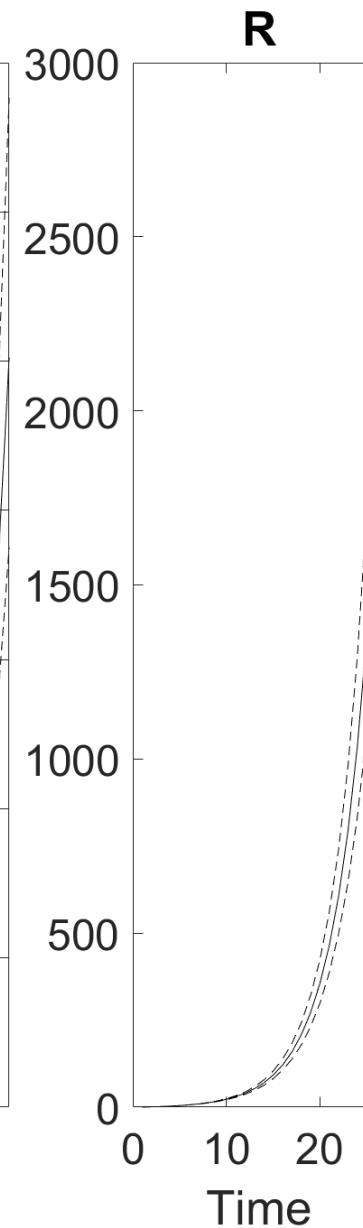
E



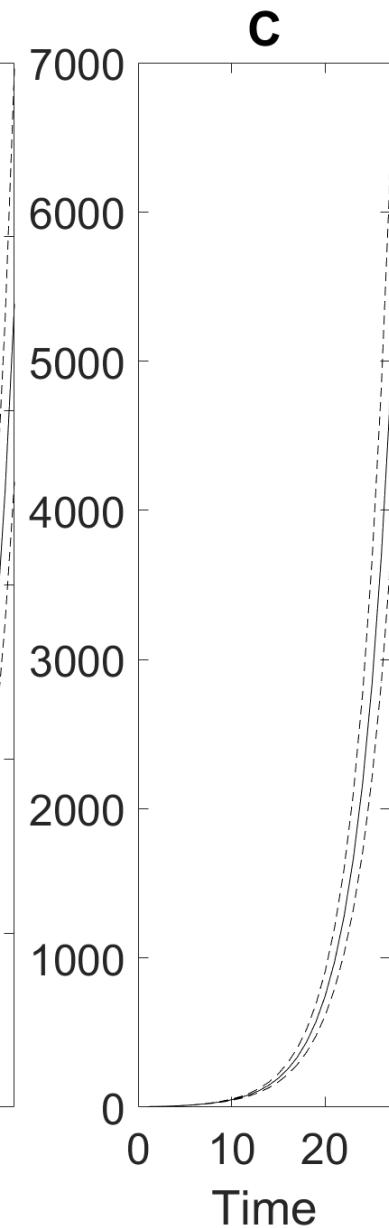
I



R



C



Model Comparison

SEIR Neg. Binomial & Exponential Neg. Binomial

Specifying the Exponential Model

```
% <=====
% < Author: Gerardo Chowell =====
% <=====

function dx=EXP(t,x,params0)

% parameters in order: r
dx=zeros(1,1);

dx(1,1)=params0(1)*x(1,1);
```

$$C'(t) = r * C(t)$$

r : Growth rate ($r > 0$)

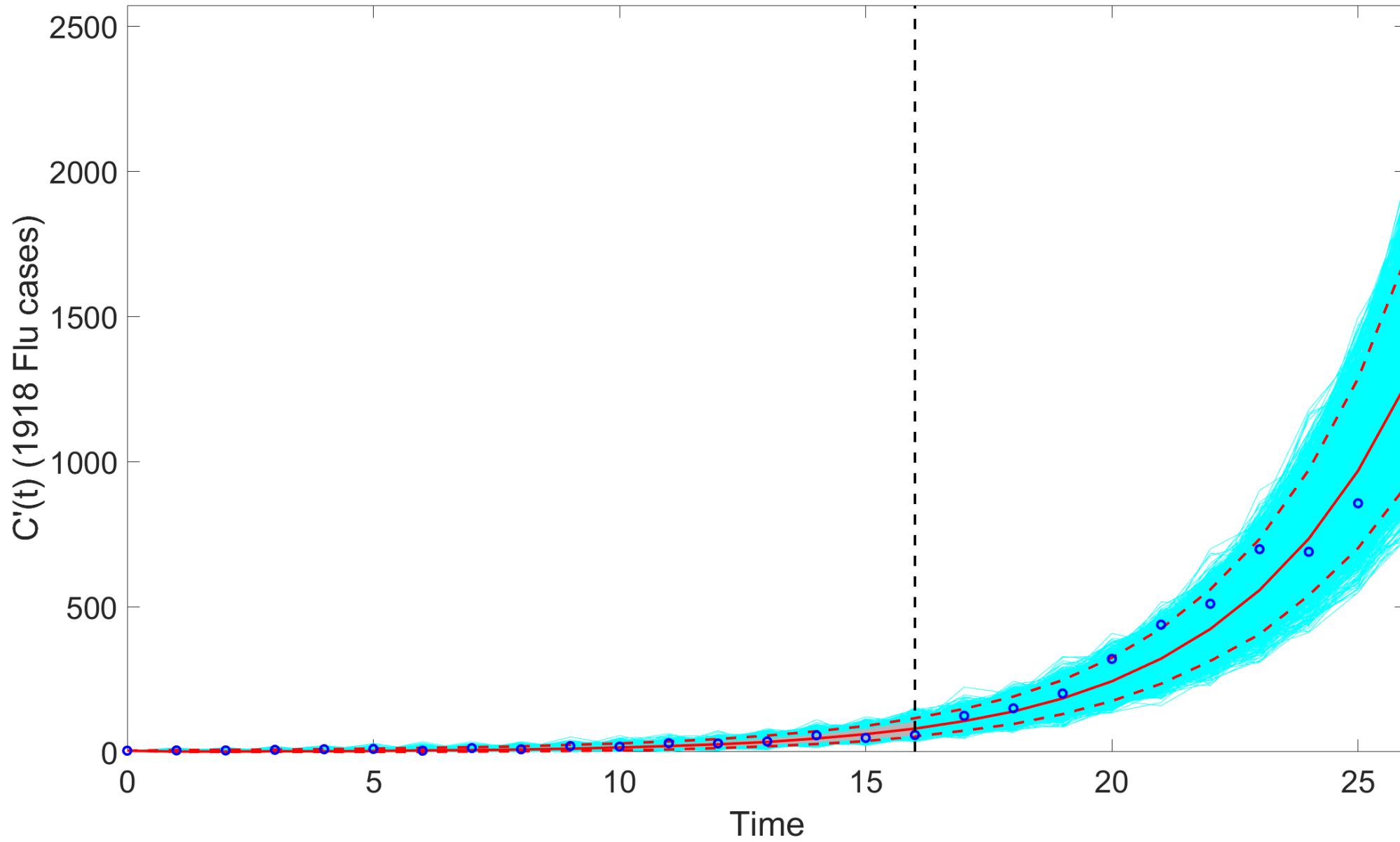
```
% <===== ODE model =====>
% <===== ODE model =====>
% <===== ODE model =====>

model.fc=@EXP; % name of the model function
model.name='EXP model'; % string indicating the name of the ODE model

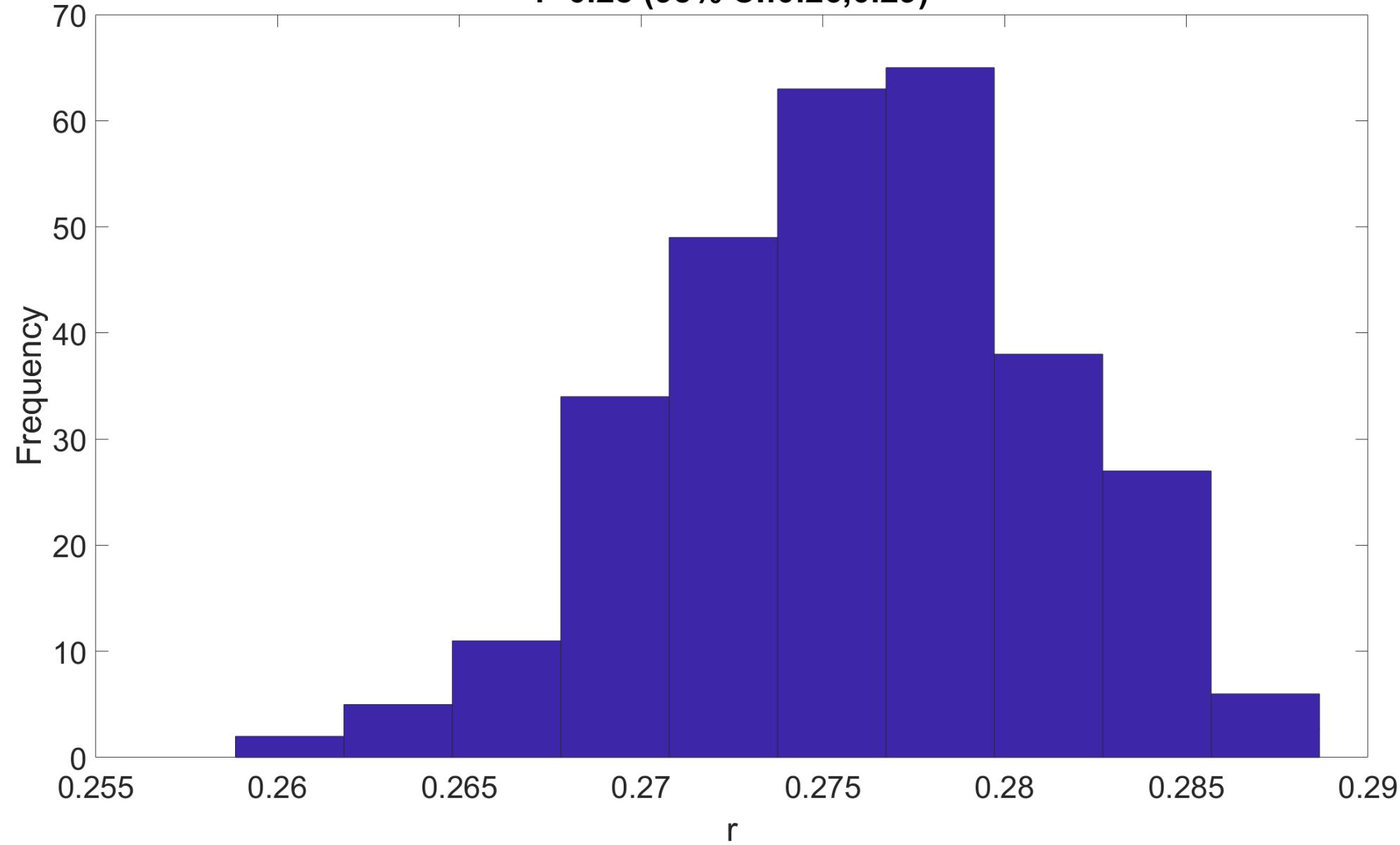
params.label={'r'}; % list of symbols to refer to the model parameters
params.LB=[0]; % lower bound values of the parameter estimates
params.UB=[10]; % upper bound values of the parameter estimates
params.initial=[0.18]; % initial parameter values/guesses
params.fixed=[0]; % Boolean vector to indicate any parameters that should remain fixed (1) to initial values indicated in par
params.fixI0=1; % Boolean variable indicating if the initial value of the fitting variable is fixed according to the first ob
params.composite=''; % Estimate a composite function of the individual model parameter estimates otherwise it is left empty.
params.composite_name=''; % Name of the composite parameter
params.extra0=[]; % used to pass any extra parameters (e.g., data, static variables) to the model function

vars.label={'C'}; % list of symbols to refer to the variables included in the model
vars.initial=5; % vector of initial conditions for the model variables
vars.fit_index=1; % index of the model's variable that will be fit to the observed time series data
vars.fit_diff=1; % boolean variable to indicate if the derivative of model's fitting variable should be fit to data.
```

EXP model

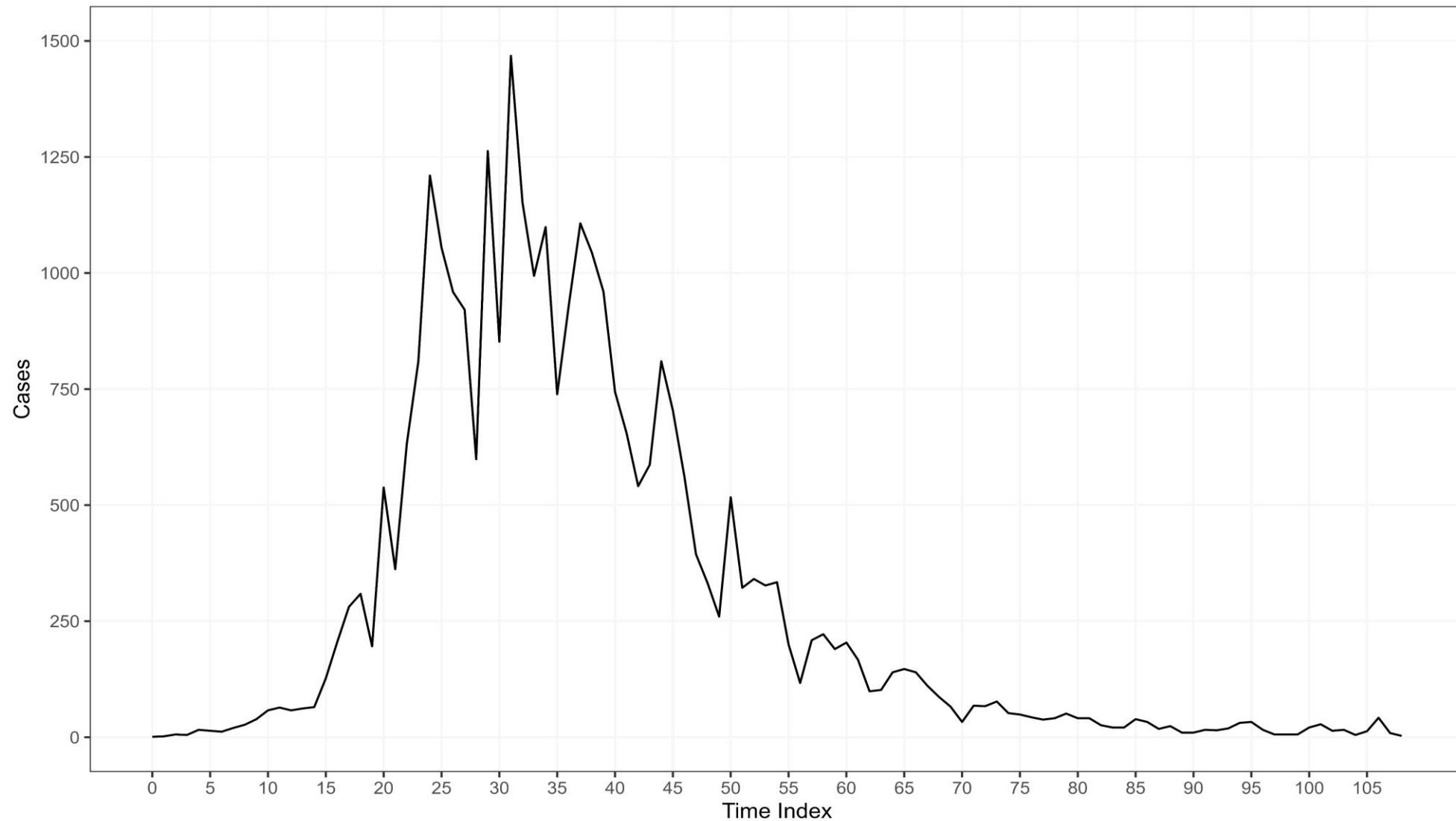


r=0.28 (95% CI:0.26,0.29)



Model	MAE	MSE	Coverage 95% PI	WIS
Calibration Performance				
SEIR model with NB error structure (<dist1>=3)	5.74	59.51	94.12	3.66
Exponential model with negative binomial error structure (<dist1>=3)	5.99	67.03	100.0	3.84
Forecast Performance				
SEIR model with NB error structure (<dist1>=3)	65.48	8058.65	70.0	49.80
Exponential model with negative binomial error structure (<dist1>=3)	79.79	9252.18	90.0	46.72

Tutorial #2: Swiss COVID-19



Daily number of reported cases of SARS-CoV-2 infection in Switzerland reported at the national level during the first wave (Feb. 2020 to June 2020).

Specifying SEIURC and R₀

Early Phase

```

% <=====
% < Author: Gerardo Chowell =====>
% <=====>

function dx=SEIRUnder(t,x,params0,extra0)

beta0=params0(1);
alpha=params0(2); % non-homogenous mixing parameter
rho=params0(3);
k=params0(4);
gamma1=params0(5);
N=params0(6);

dx=zeros(6,1); % define the vector of the state derivatives: S, E, I, U, R, C

dx(1,1)= -beta0*x(1,1).*((x(3,1)+x(4,1)).^alpha)./N; %S

dx(2,1)= beta0*x(1,1).*((x(3,1)+x(4,1)).^alpha)./N - k*x(2,1); %E

dx(3,1)= k*rho*x(2,1) - gamma1*x(3,1); %I

dx(4,1)= k*(1-rho)*x(2,1) - gamma1*x(4,1); %U

dx(5,1)= gamma1*(x(3,1)+x(4,1)); %R

dx(6,1)= k*rho*x(2,1); %C

```

$$\begin{cases} \dot{S} = -\beta S(t) \frac{I(t) + U(t)^\alpha}{N} \\ \dot{E} = \beta S(t) \frac{I(t) + U(t)^\alpha}{N} - \kappa E(t) \\ \dot{I} = \kappa \rho E(t) - \gamma I(t) \\ \dot{U} = \kappa (1 - \rho) E(t) - \gamma U(t) \\ \dot{R} = \gamma (I(t) + U(t)) \\ \dot{C} = \kappa \rho E(t) \end{cases}$$

```
% <===== ODE model =====>
% <===== ODE model =====>
% <===== ODE model =====>

model.fc=@SEIR_unreported; % name of the model function
model.name='SEIR swiss_covid underreporting'; % string indicating the name of the ODE model

params.label={'\beta_0','\alpha','\rho','\kappa','\gamma','N'}; % list of symbols to refer to the model parameters
params.LB=[0.001 0.5 0.01 0.01 0.01 47332614]; % lower bound values of the parameter estimates
params.UB=[5 1 1 1 1 47332614]; % upper bound values of the parameter estimates
params.initial=[0.6 1 1 1/5 1/4 47332614]; % initial parameter values/guesses
params.fixed=[0 1 0 1 1 1]; % Boolean vector to indicate any parameters that should remain fixed (1) to initial values in
params.fixI0=1; % Boolean variable indicating if the initial value of the fitting variable is fixed according to the first
params.composite=@R0s_unreported; % Estimate a composite function of the individual model parameter estimates otherwise
params.composite_name='R0s_unreported'; % Name of the composite parameter
params.extra0='';

vars.label={'S','E','I','U','R','C'}; % list of symbols to refer to the variables included in the model
vars.initial=[params.initial(6)-1 0 1 0 0 1]; % vector of initial conditions for the model variables
vars.fit_index=6; % index of the model's variable that will be fit to the observed time series data
vars.fit_diff=1; % boolean variable to indicate if the derivative of model's fitting variable should be fit to data.
```

Preparing options_fit.m & options_forecast.m

Fitting and forecasting the early growth phase (First 20-days)

```
% <===== Declare global variables =====>
% <===== Declare global variables =====>
% <===== Declare global variables =====>

global method1 % Parameter estimation method

% <===== Datasets properties =====>
% <===== Datasets properties =====>
% <===== Datasets properties =====>
% Located in the input folder, the time series data file is a text file with extension *.txt.
% The time series data file contains the incidence curve of the epidemic of interest.
% The first column corresponds to time index: 0,1,2, ... and the second
% column corresponds to the observed time series data.

cadfilename1='curve-covid-firstwave-swiss-reporteddt';
caddisease='COVID-19'; % string indicating the name of the disease related to the time series data
datatype='cases'; % string indicating the nature of the data (cases, deaths, hospitalizations, etc)
```

```

% <===== Parameter estimation =====>
% <===== Parameter estimation =====>
% <===== Parameter estimation =====>

method1=0; % Type of estimation method

% Nonlinear least squares (LSQ)=0,
% MLE Poisson=1,
% MLE (Neg Binomial)=3, with VAR=mean+alpha*mean;
% MLE (Neg Binomial)=4, with VAR=mean+alpha*mean^2;
% MLE (Neg Binomial)=5, with VAR=mean+alpha*mean^d;

dist1=0; % Define dist1 which is the type of error structure. See below:

%dist1=0; % Normal distribution to model error structure (method1=0)
%dist1=1; % Poisson error structure (method1=0 OR method1=1)
%dist1=2; % Neg. binomial error structure where var = factor1*mean where
    % factor1 is empirically estimated from the time series
    % data (method1=0)
%dist1=3; % MLE (Neg Binomial) with VAR=mean+alpha*mean (method1=3)
%dist1=4; % MLE (Neg Binomial) with VAR=mean+alpha*mean^2 (method1=4)
%dist1=5; % MLE (Neg Binomial)with VAR=mean+alpha*mean^d (method1=5)

switch method1
    case 1
        dist1=1;
    case 3
        dist1=3;
    case 4
        dist1=4;
    case 5
        dist1=5;
end

numstartpoints=2*4^2; % Number of initial guesses for optimization procedure using MultiStart
B=300; % number of bootstrap realizations to characterize parameter uncertainty

```

Tutorial

- As the case counts are much higher compared to Tutorial #1, we will be using nonlinear least squares (NLSQ) and assuming a normal error distribution.
- Using 32 start points ($\langle \text{numstartpoints} \rangle = 32$)
- Using 300 bootstrap realizations to characterize parameter uncertainty ($\langle B \rangle = 300$)

Fitting to the first 20 days

```
% <===== Forecasting parameters =====>
% <===== Parameters of the rolling window analysis =====>
% <=====>

getperformance=1; % flag or indicator variable (1/0) to calculate forecasting performance or not

forecastingperiod=10; % forecast horizon (number of time units ahead)

windowsize1=20; % moving window size

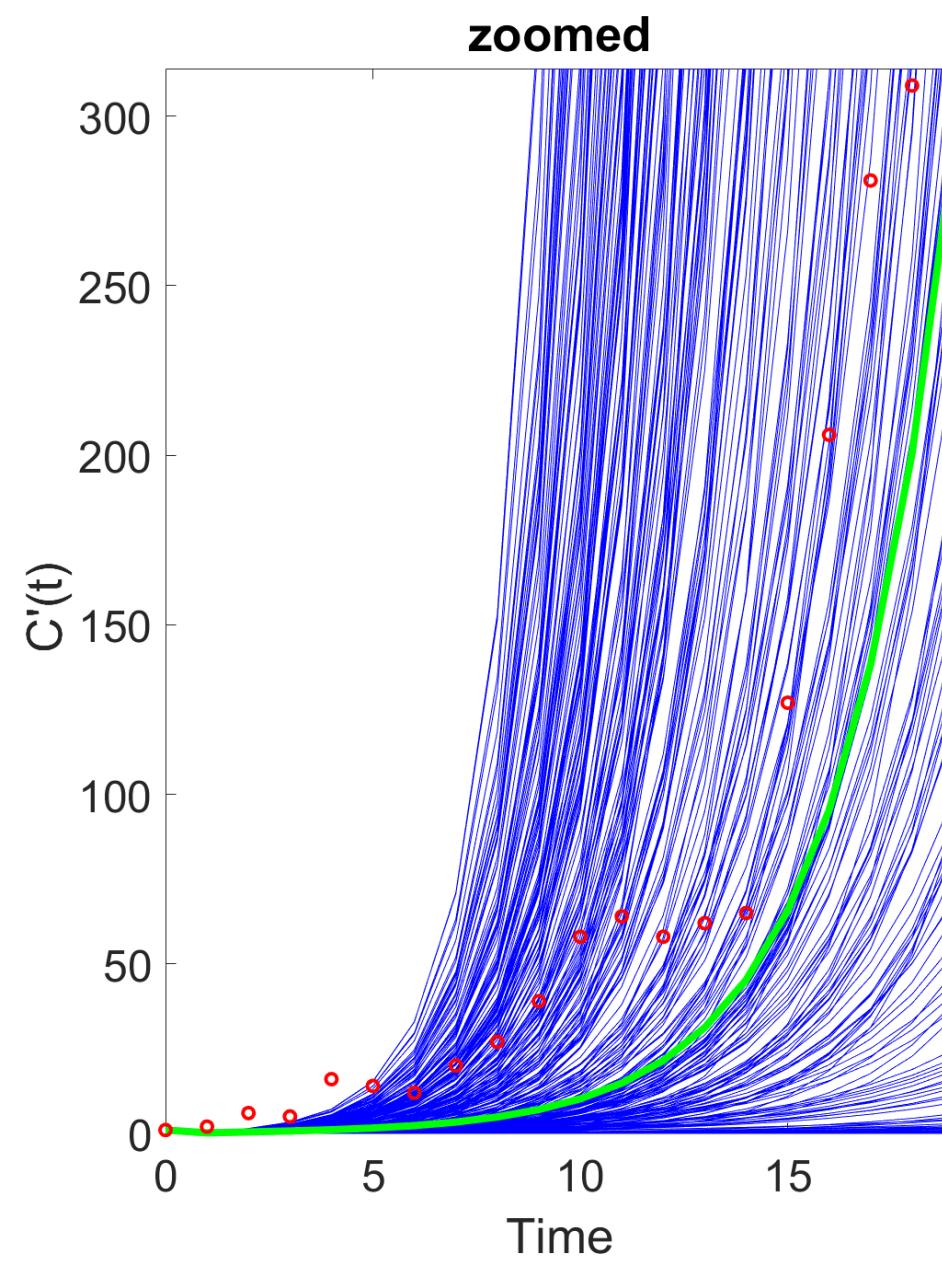
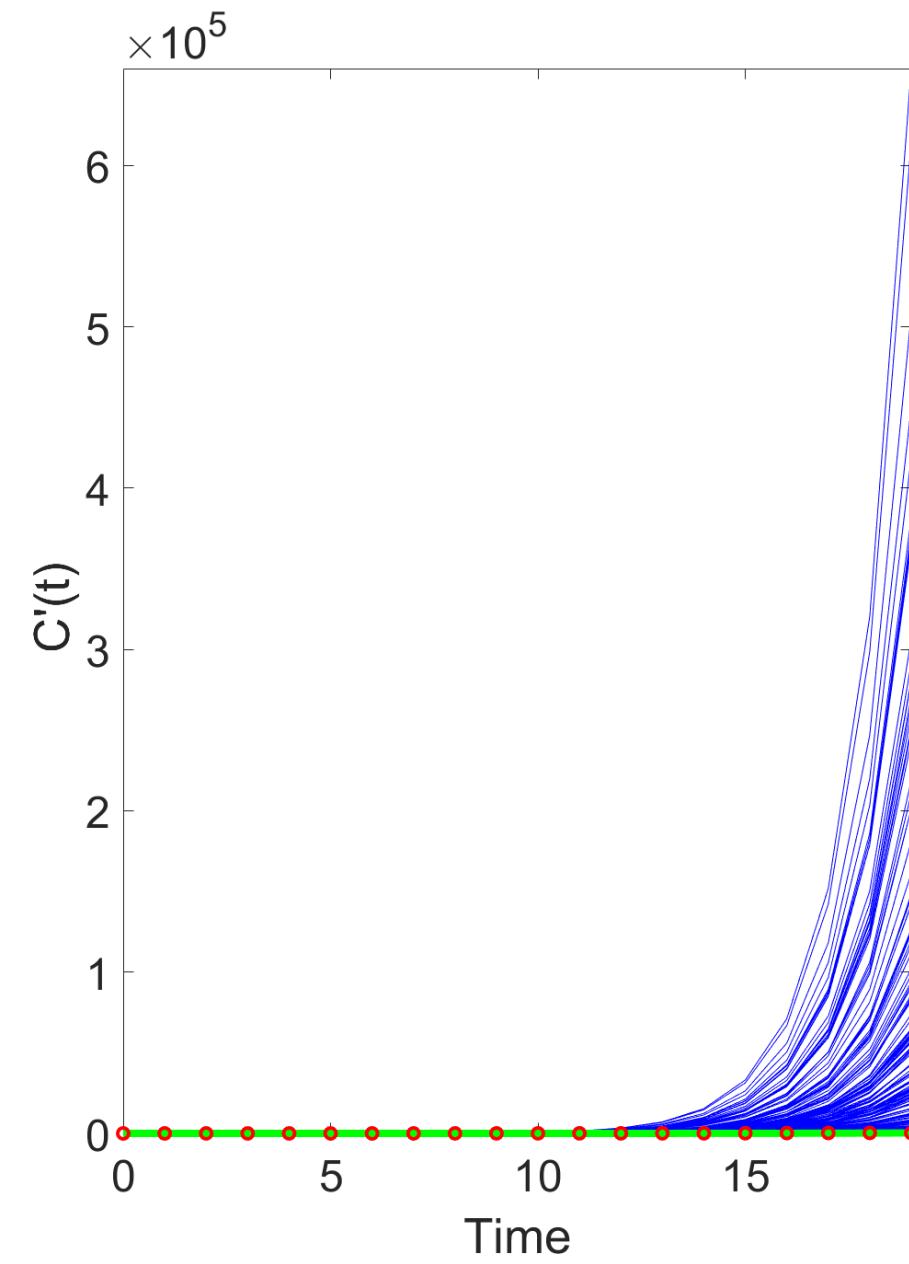
tstart1=1; % time point for the start of rolling window analysis

tend1=1; %time point for the end of the rolling window analysis

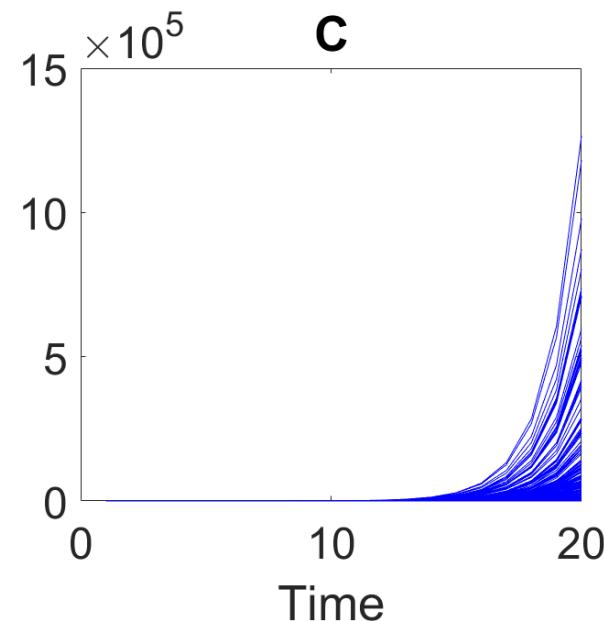
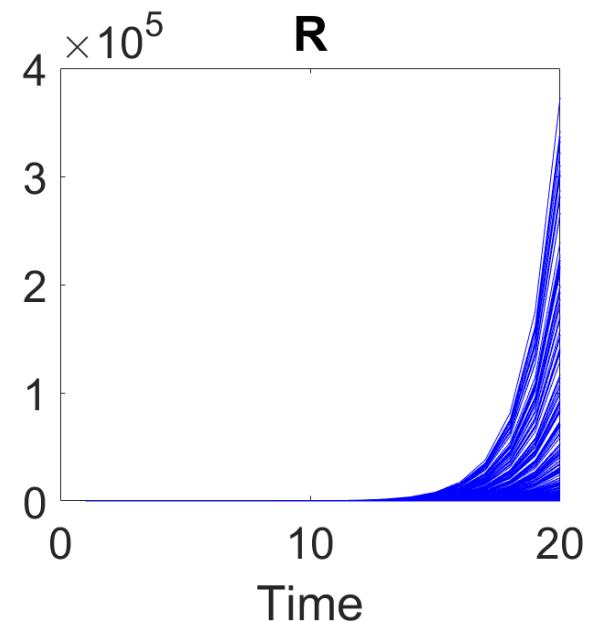
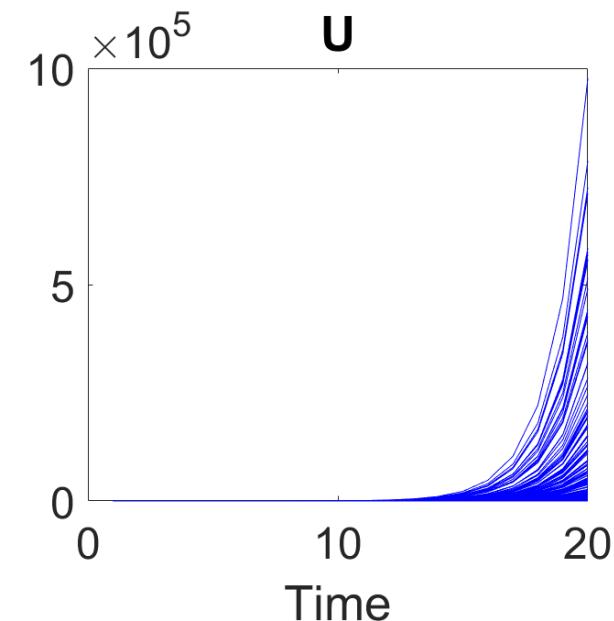
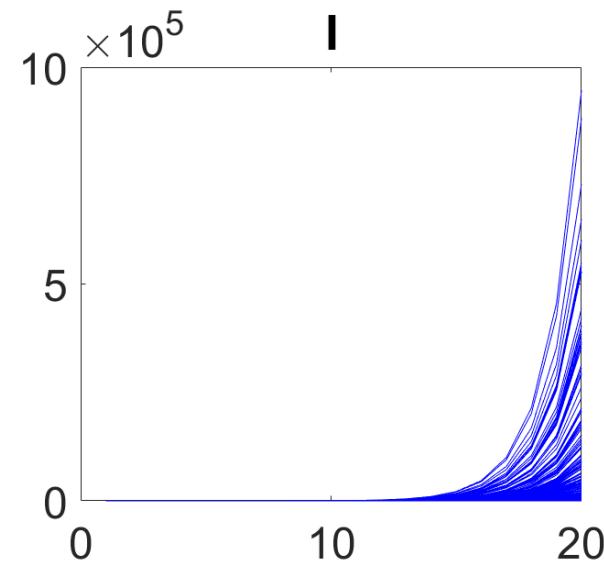
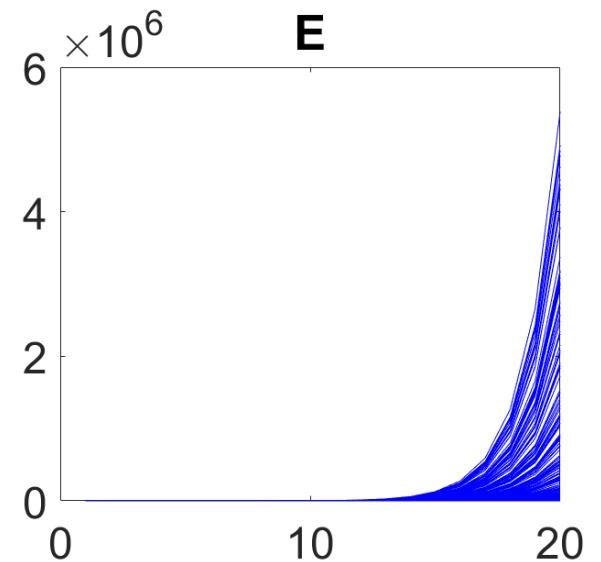
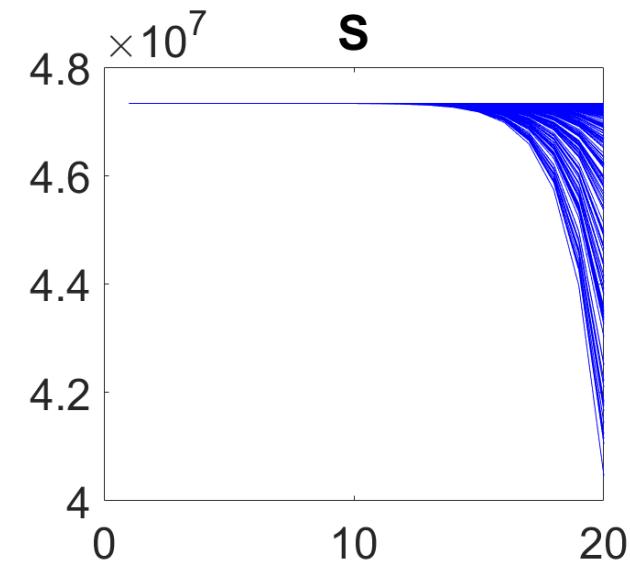
printscreen1=1;
```

Generating preliminary model solutions

```
plotODEModel(@options_fit_SEIR_unreportedNIn_covid_s  
wiss_dist1_0)
```



Fixed α

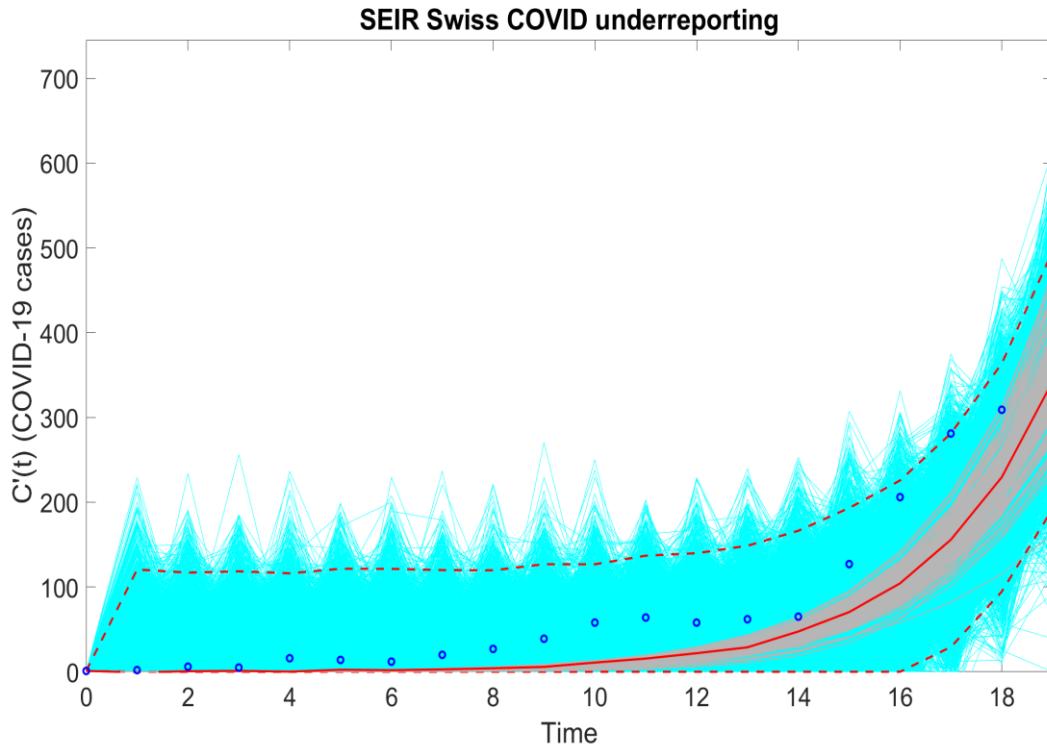


Fixed α

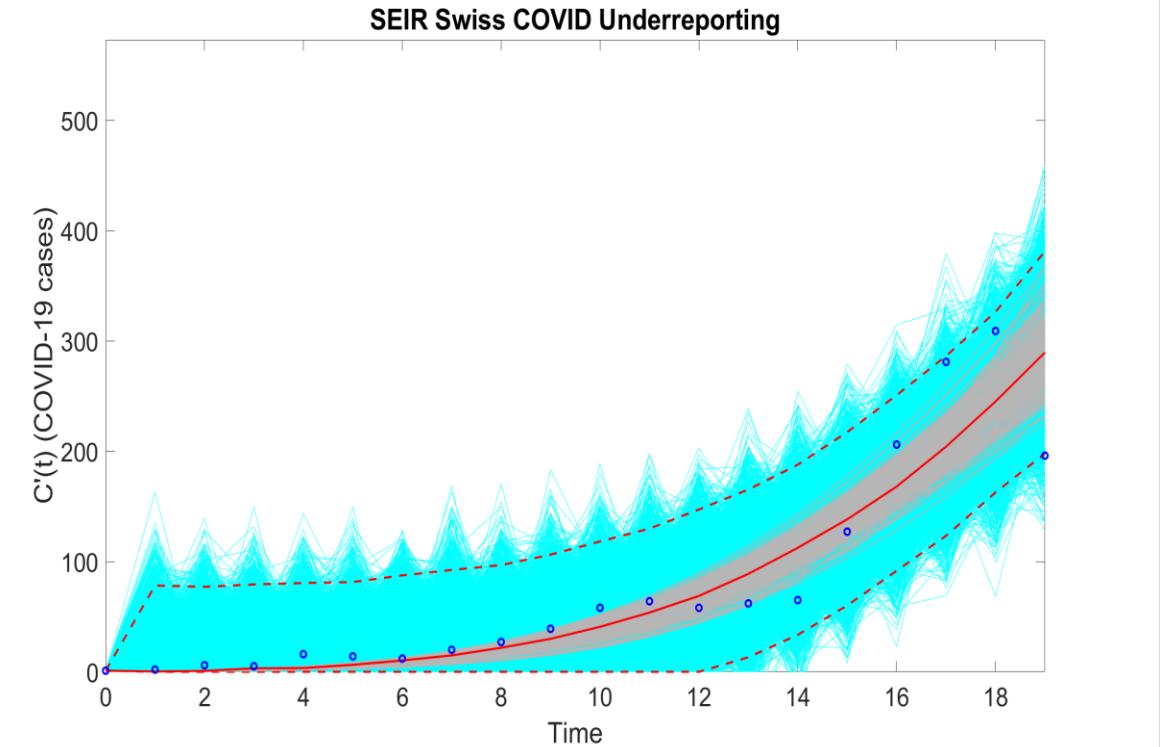
Fitting, plotting, and evaluating the model with quantified uncertainty

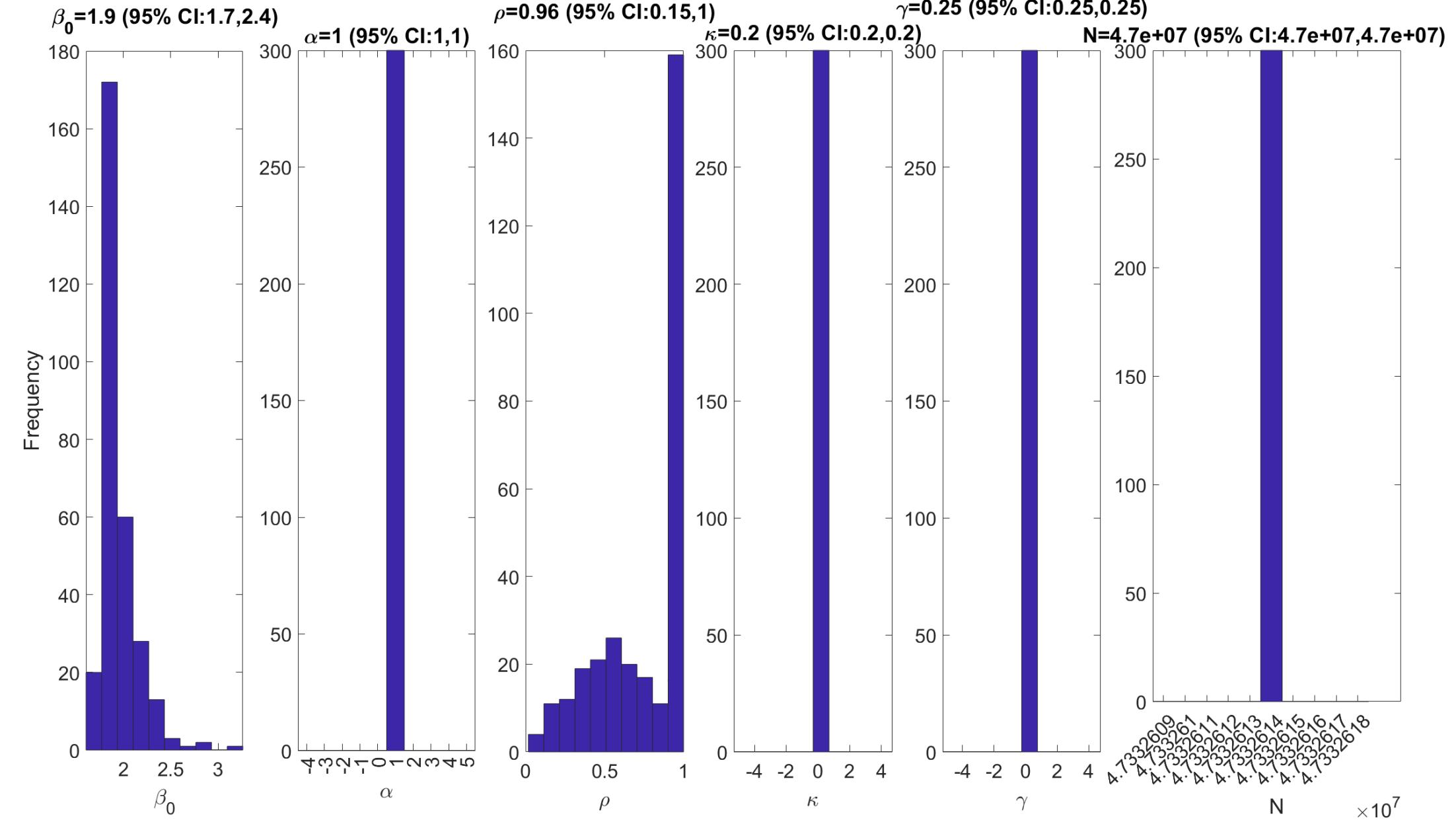
```
(1) Run_Fit_ODEModel(@options_fit_SEIR_unreportedNIn  
                      _covid_swiss_dist1_0, 1, 1, 20)  
(2) plotFit_ODEModel(@options_fit_SEIR_unreportedNIn  
                      _covid_swiss_dist1_0, 1, 1, 20)
```

Fixed α

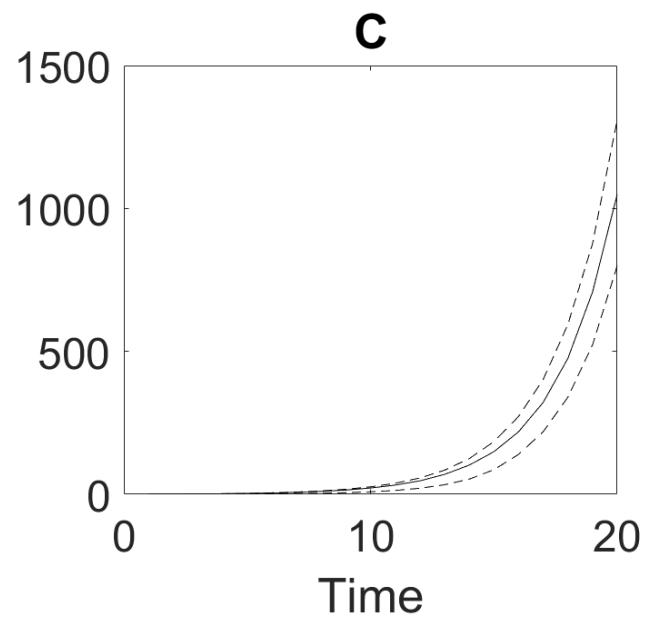
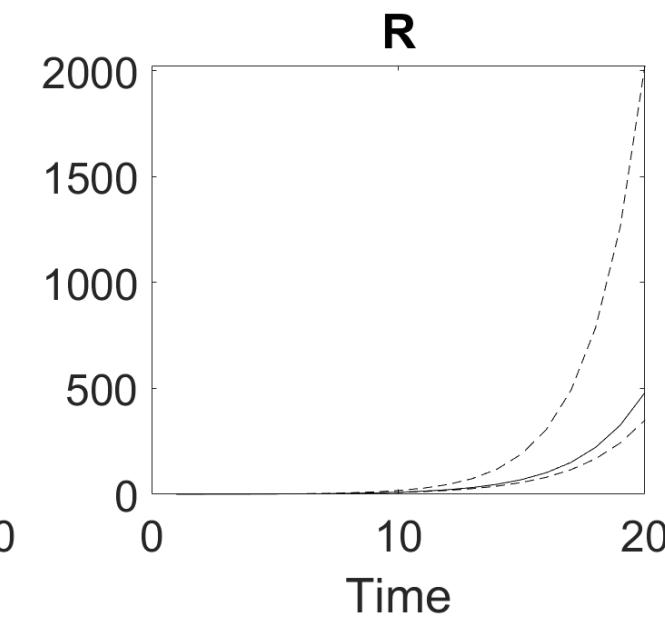
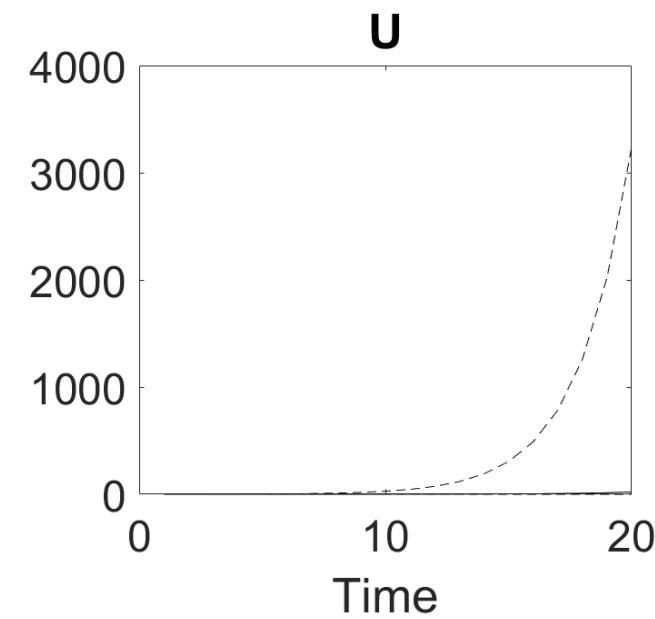
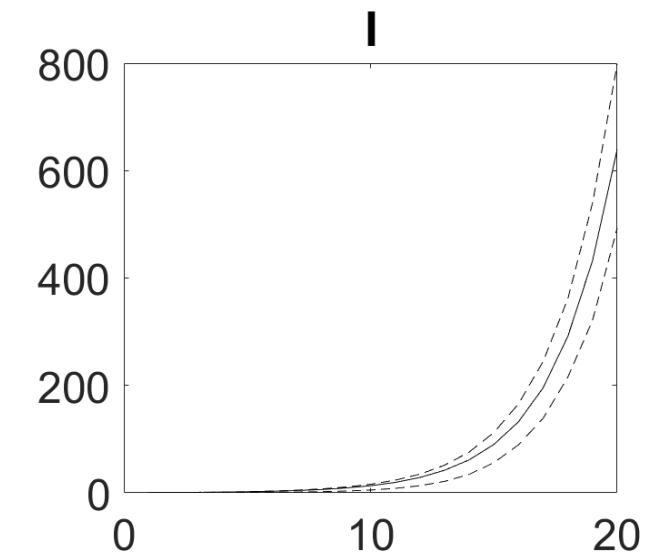
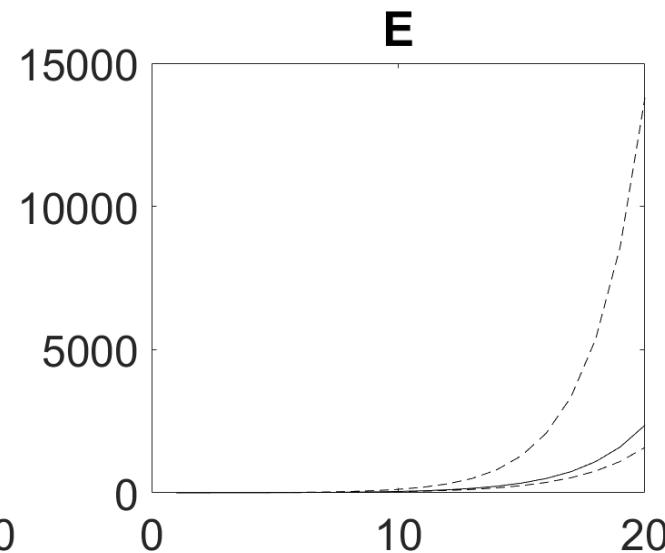
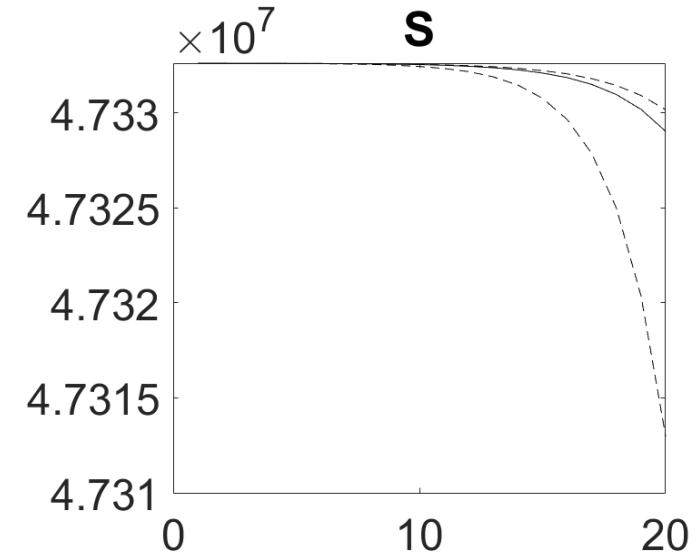


Estimated α



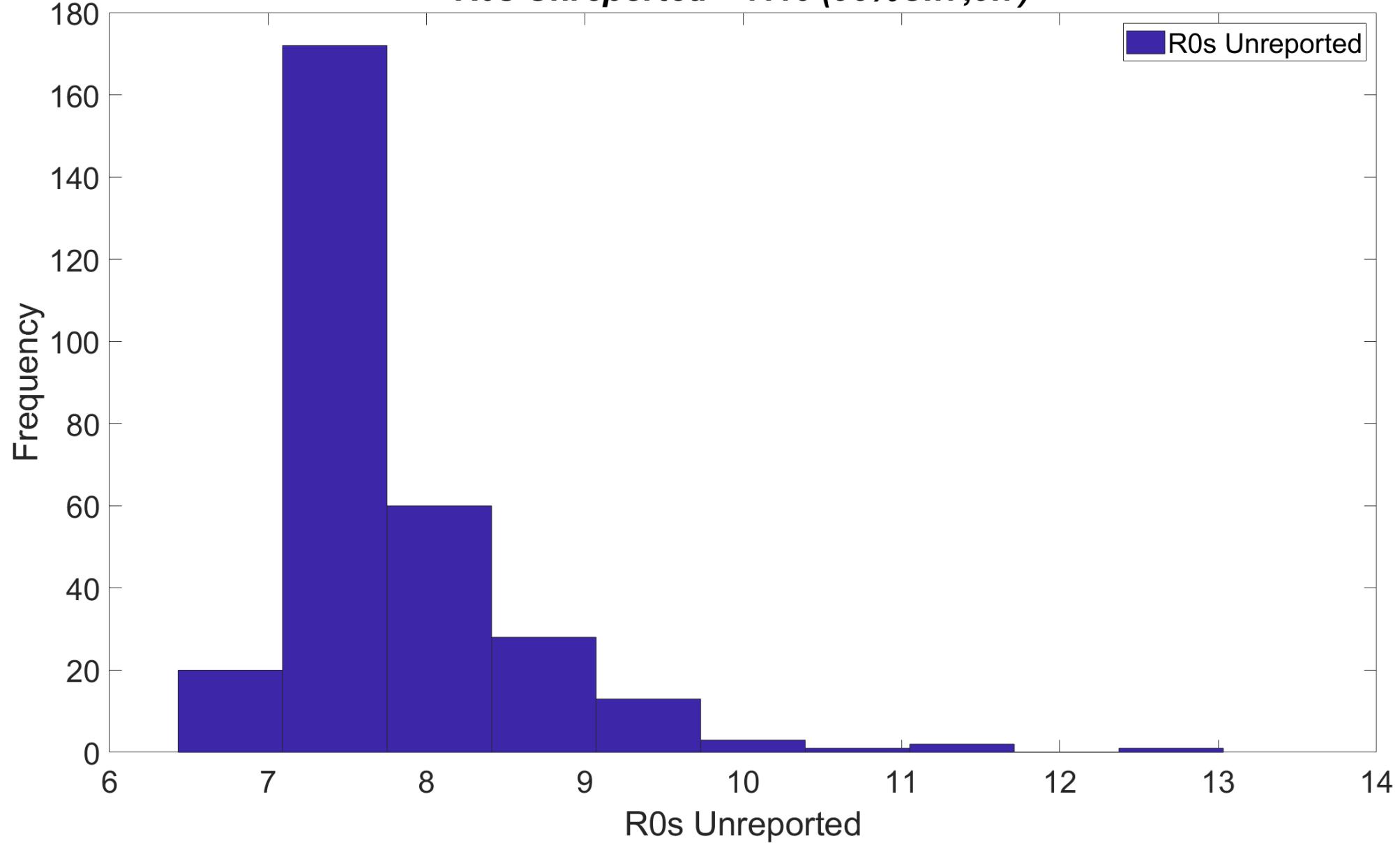


Fixed α



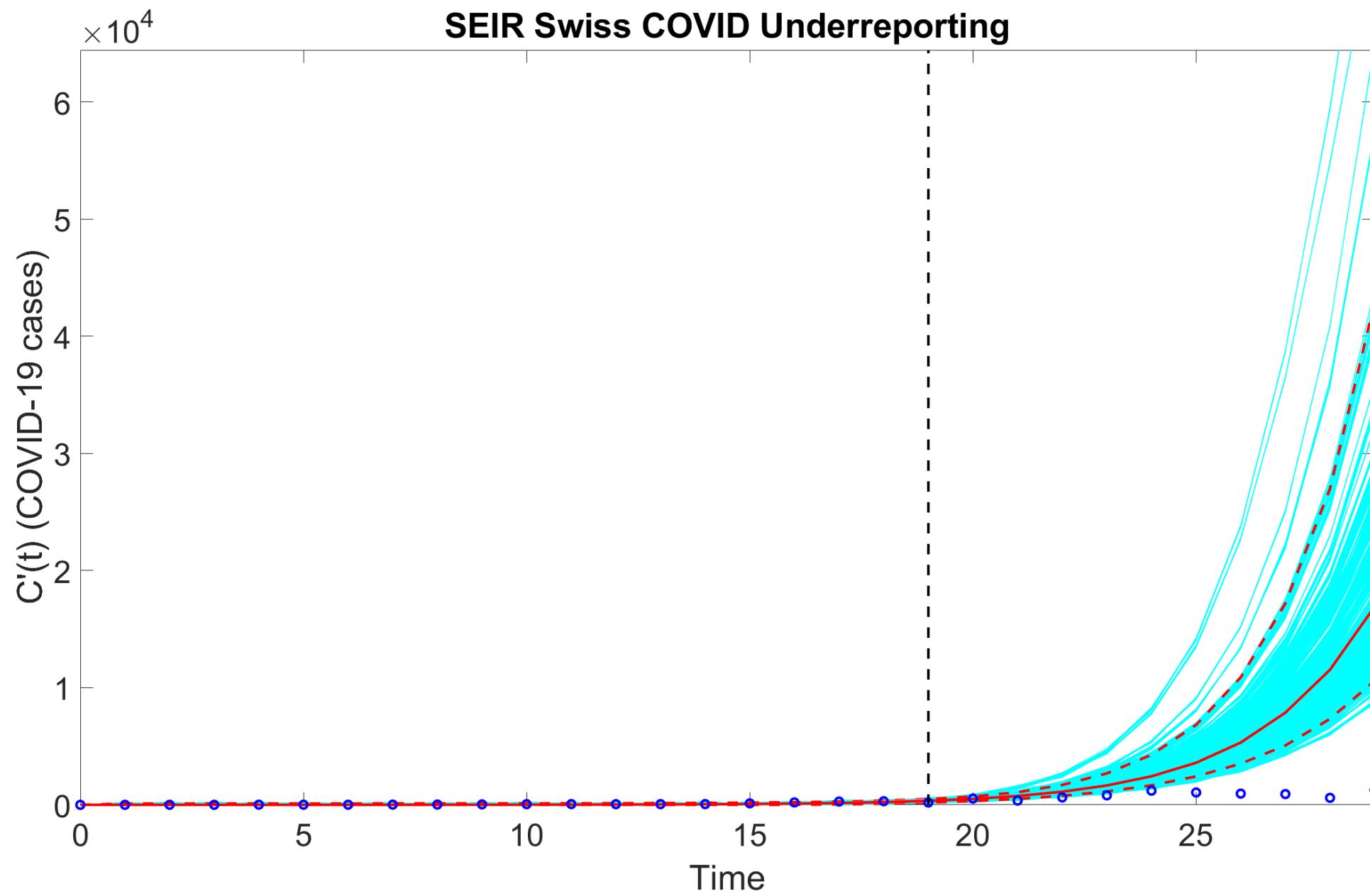
Fixed α

R0s Unreported = 7.46 (95%CI:7,9.7)

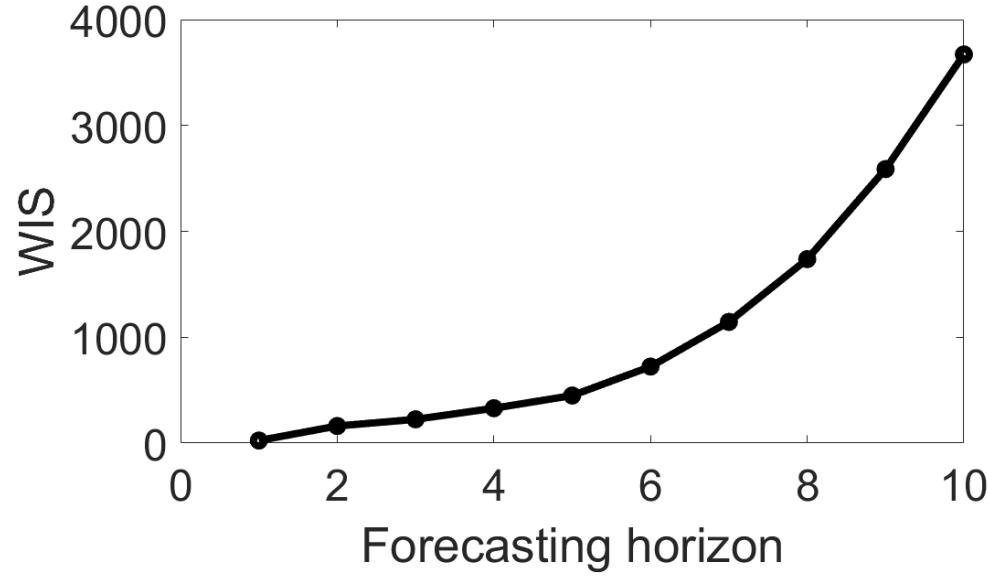
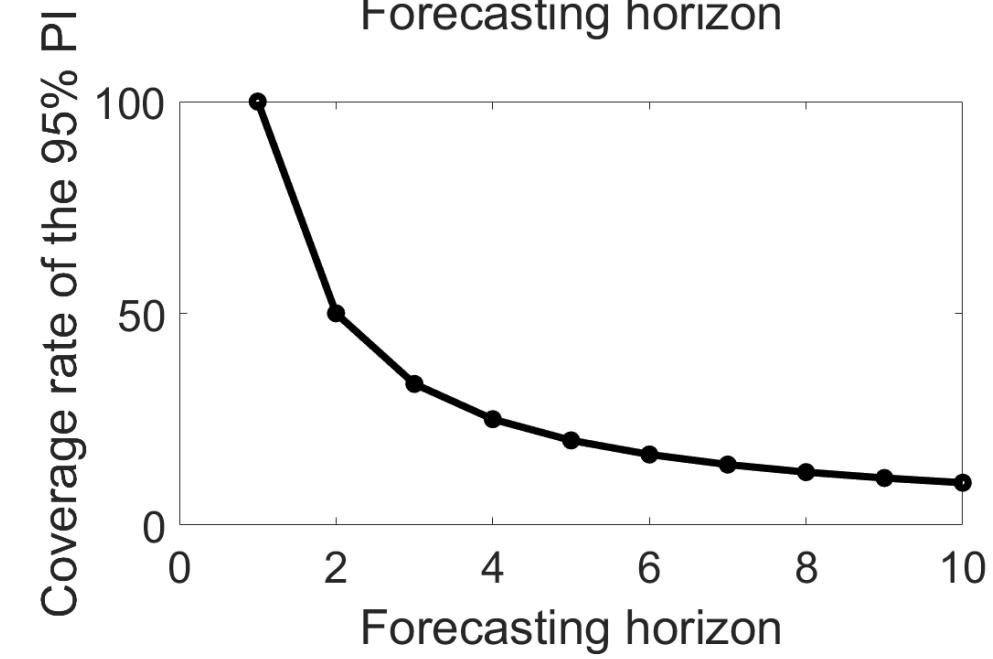
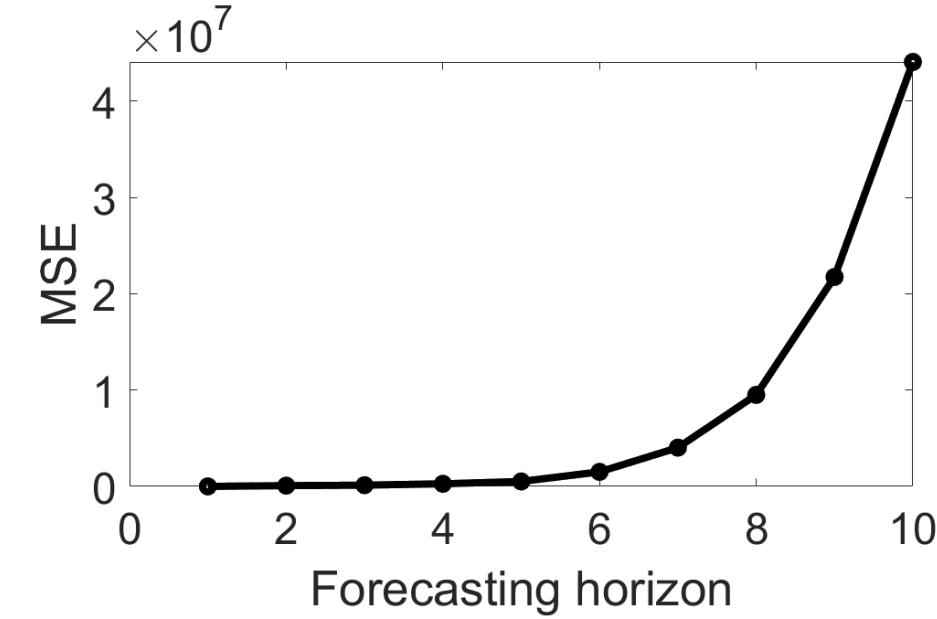
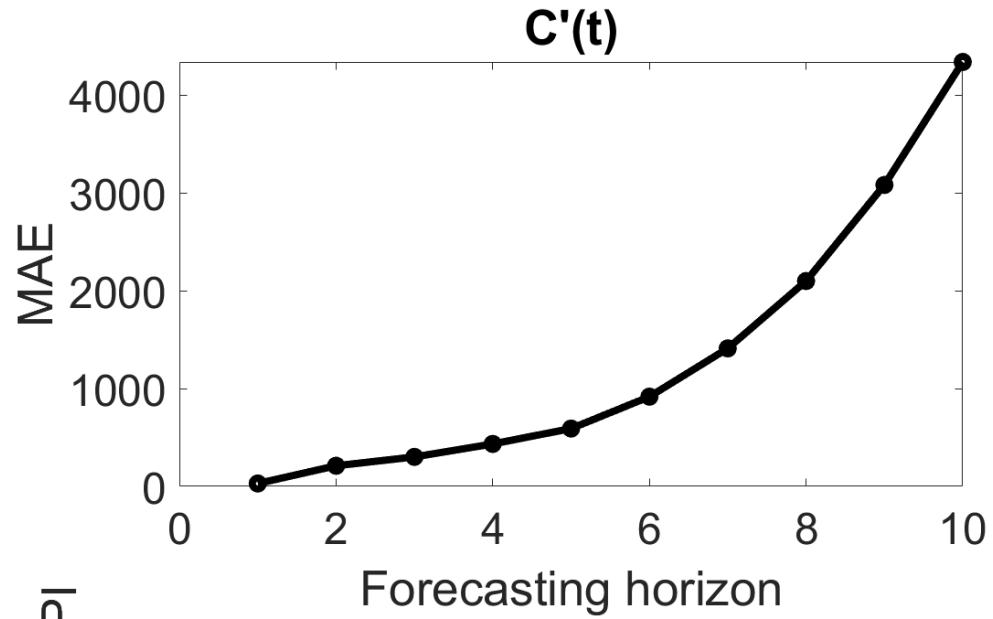


Generating, plotting and assessing model-based forecasts

```
(1) Run_Forecasting_ODEModel(@options_forecast_SEIR_
    unreportedNIn_covid_swiss_dist1_0, 1, 1, 20,10)
(2) plotForecast_ODEModel(@options_forecast_SEIR_unr
    eportedNIn_covid_swiss_dist1_0, 1, 1, 20,10)
```



Fixed α



Fixed α

Model Comparison (Early Phase)

SEIUR Normal, GGM Normal & RICH Normal

Specifying the GGM Model

```
% <=====
% < Author: Gerardo Chowell =====
% <=====

function dx=GGM(t,x,params0,extra0)

% parameters in order: r, p

dx=zeros(1,1);

dx(1,1)=params0(1)*x(1,1).^params0(2);
```

$$C'(t) = rC(t)^p$$

r : Growth rate ($r > 0$)
 p : Scaling of growth parameter

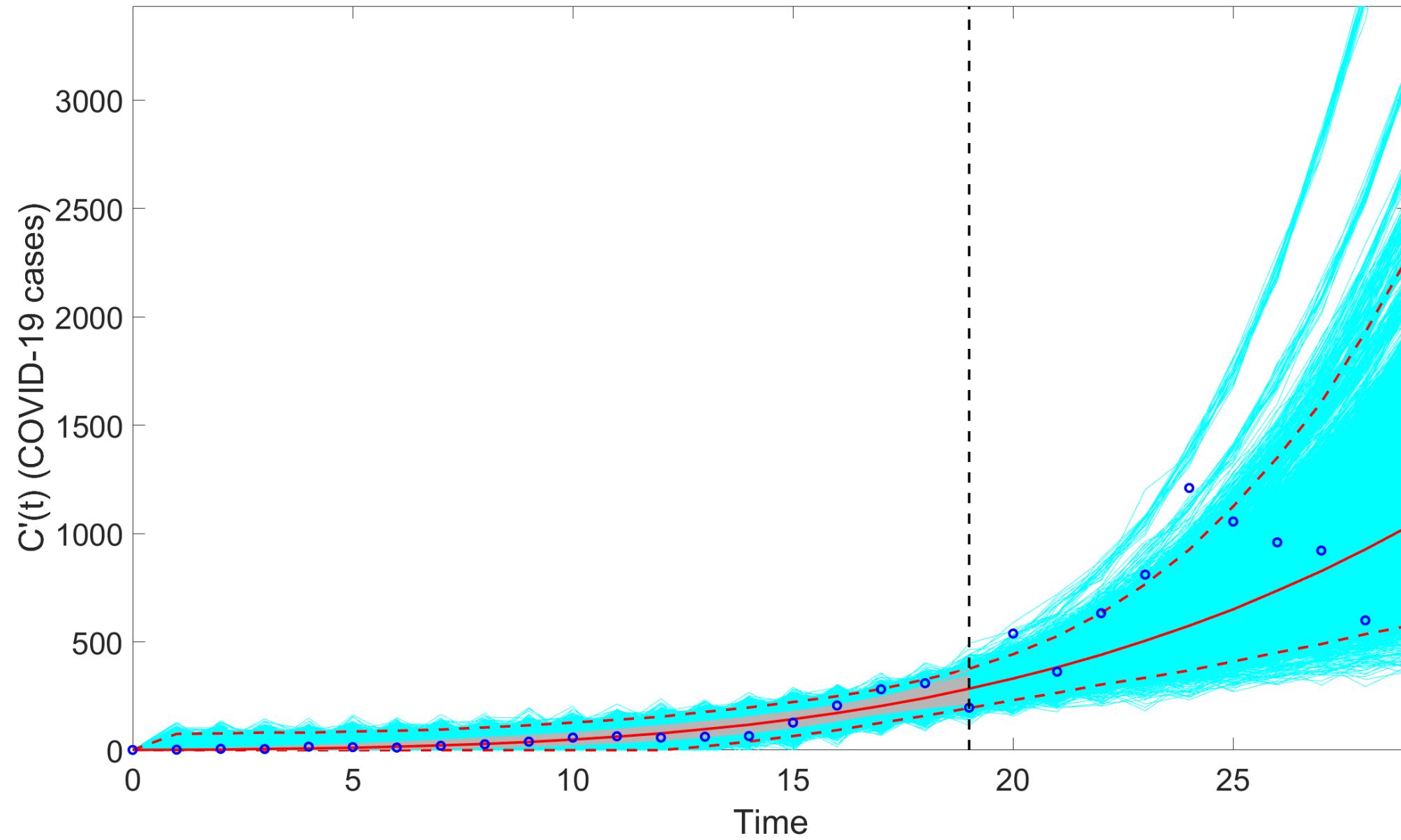
```
% <===== ODE model =====>
% <===== ODE model =====>
% <===== ODE model =====>

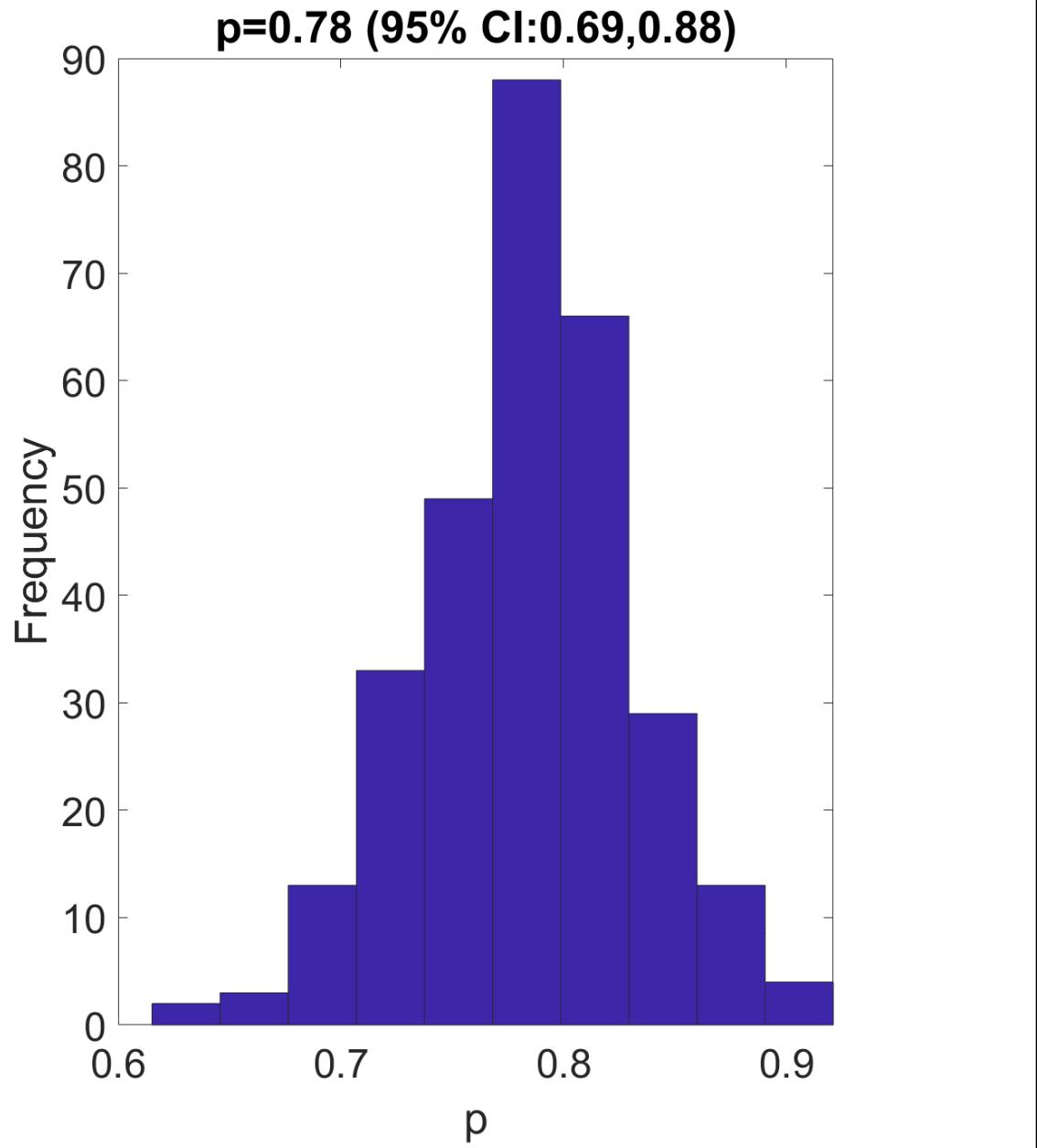
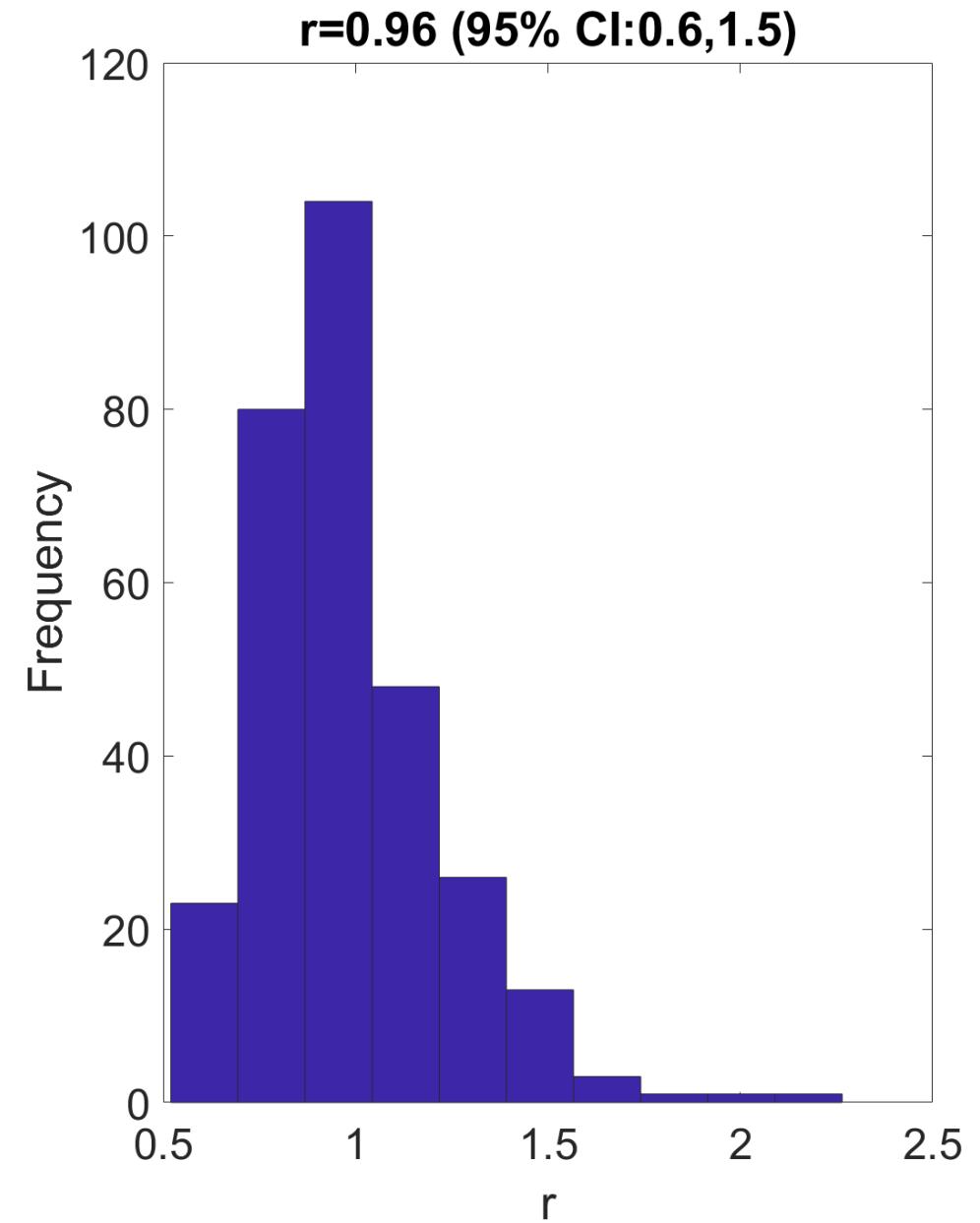
model.fc=@GGM; % name of the model function
model.name='GGM model'; % string indicating the name of the ODE model

params.label={'r', 'p'}; % list of symbols to refer to the model parameters
params.LB=[0 0]; % lower bound values of the parameter estimates
params.UB=[10 1]; % upper bound values of the parameter estimates
params.initial=[0.91 0.79]; % initial parameter values/guesses
params.fixed=[0 0]; % Boolean vector to indicate any parameters that should remain fixed (1) to initial values indicated above
params.fixI0=1; % Boolean variable indicating if the initial value of the fitting variable is fixed according to the fixed parameter
params.composite=''; % Estimate a composite function of the individual model parameter estimates otherwise it is left empty
params.composite_name=''; % Name of the composite parameter
params.extra0=[]; % used to pass any extra parameters (e.g., data, static variables) to the model function

vars.label={'C'}; % list of symbols to refer to the variables included in the model
vars.initial=5; % vector of initial conditions for the model variables
vars.fit_index=1; % index of the model's variable that will be fit to the observed time series data
vars.fit_diff=1; % boolean variable to indicate if the derivative of model's fitting variable should be fit to data.
```

GGM model





Specifying the RICH Model

```
% <=====
% < Author: Gerardo Chowell =====
% <=====

function dx=RICH(t,x,params0,extra0)

% parameters in order: r, a, K0

dx=zeros(1,1);

dx(1,1)=params0(1)*x(1,1)*(1-(x(1,1)/params0(3)).^params0(2));
```

$$C'(t) = rC(t)[1 - \left(\frac{C(t)}{K_0}\right)^a]$$

a : Growth rate ($r > 0$)

p : Scaling of growth parameter

K_0 : Final cumulative epidemic size

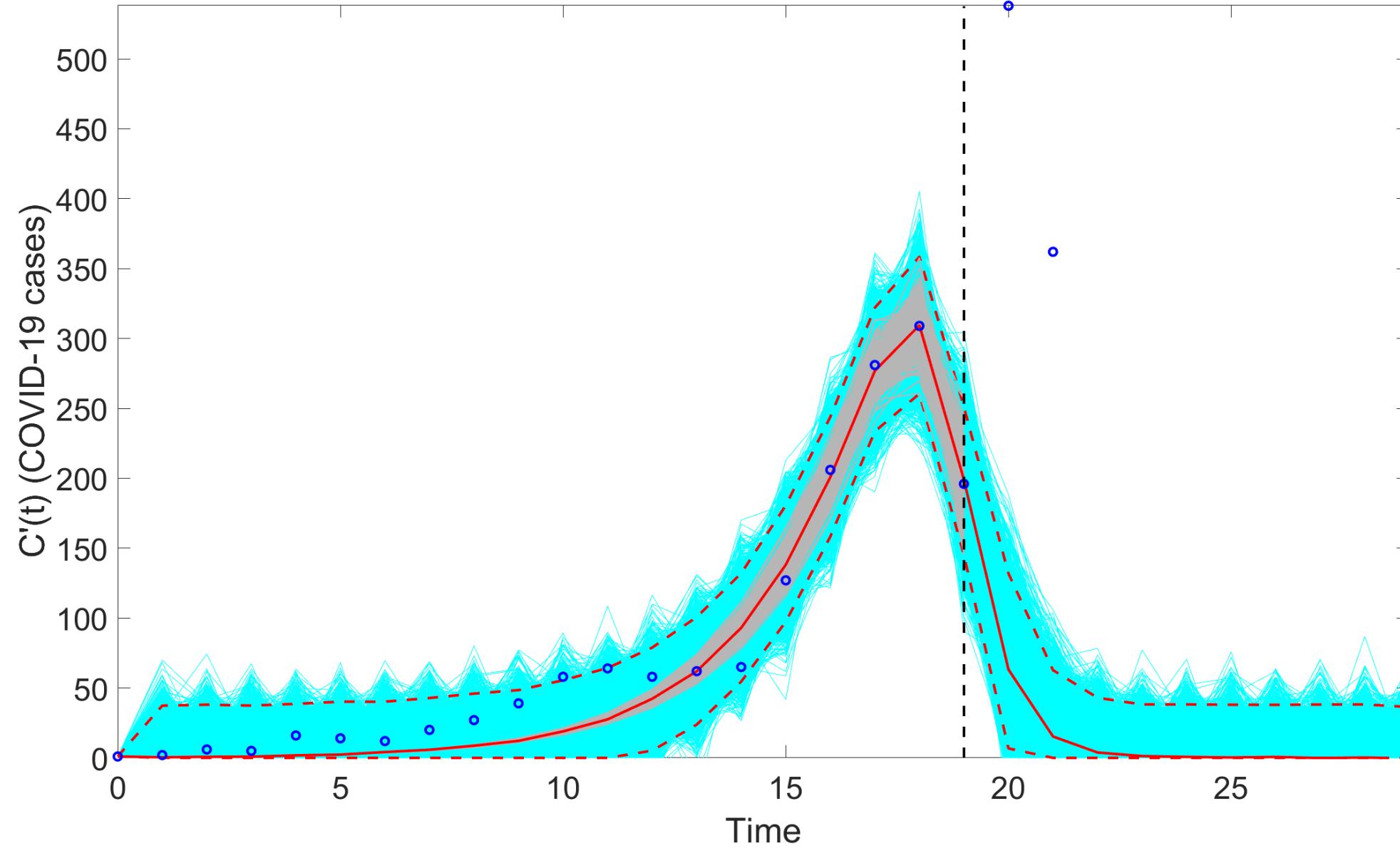
```
% <===== ODE model =====>
% <===== ODE model =====>
% <===== ODE model =====>

model.fc=@RICH; % name of the model function
model.name='RICH model'; % string indicating the name of the ODE model

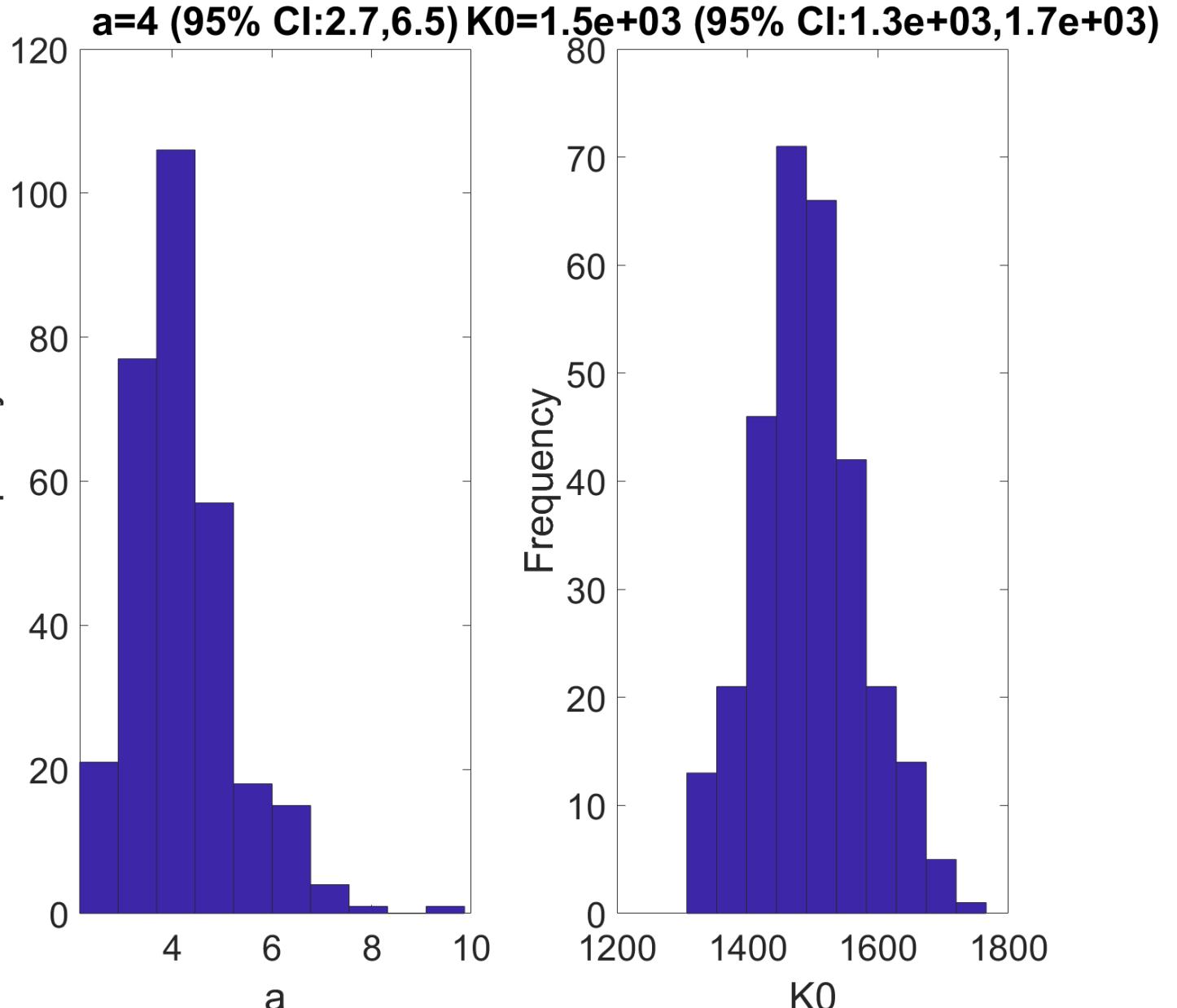
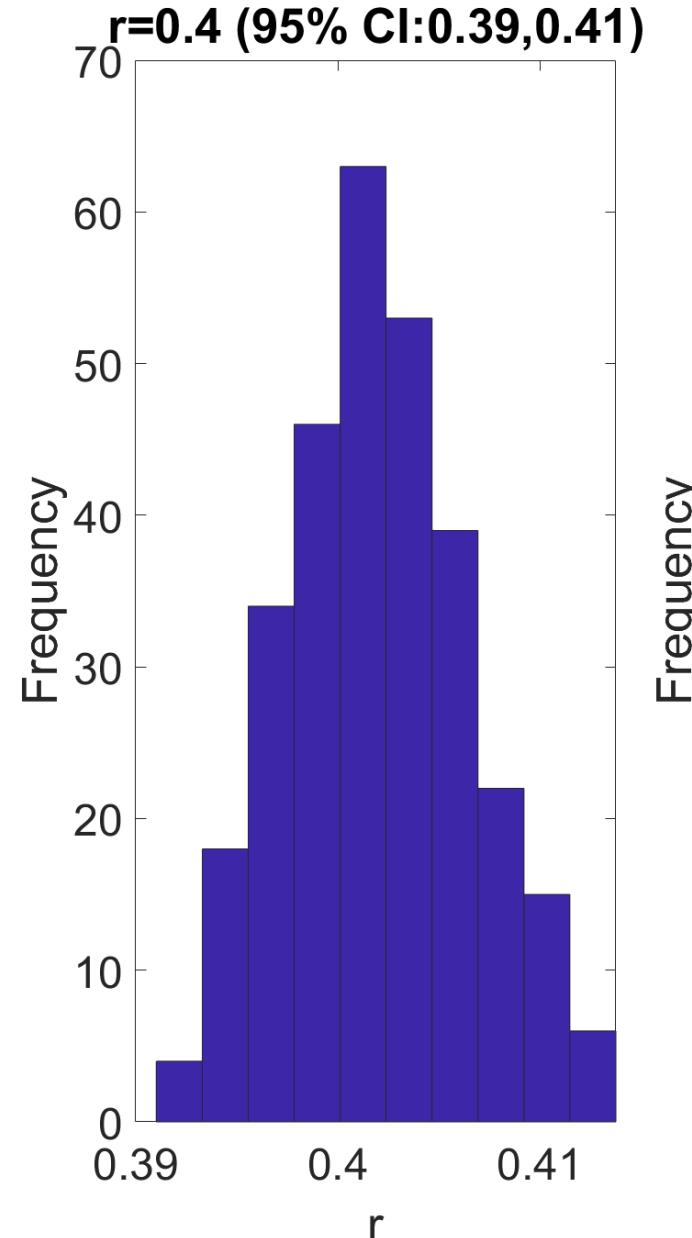
params.label={'r', 'a', 'K0'}; % list of symbols to refer to the model parameters
params.LB=[0 0 10]; % lower bound values of the parameter estimates
params.UB=[10 10 40000]; % upper bound values of the parameter estimates
params.initial=[0.91 0.79 30994]; % initial parameter values/guesses
params.fixed=[0 0 0]; % Boolean vector to indicate any parameters that should remain fixed (1) to initial values indicated above
params.fixI0=1; % Boolean variable indicating if the initial value of the fitting variable is fixed according to the fixed vector
params.composite=''; % Estimate a composite function of the individual model parameter estimates otherwise it is left empty
params.composite_name=''; % Name of the composite parameter
params.extra0=[]; % used to pass any extra parameters (e.g., data, static variables) to the model function

vars.label={'C'}; % list of symbols to refer to the variables included in the model
vars.initial=5; % vector of initial conditions for the model variables
vars.fit_index=1; % index of the model's variable that will be fit to the observed time series data
vars.fit_diff=1; % boolean variable to indicate if the derivative of model's fitting variable should be fit to data.
```

RICH model



$r=0.4$ (95% CI:0.39,0.41)



Model	MAE	MSE	Coverage 95% PI	WIS
Calibration Performance				
SEIUR model with NLSQ/ Normal error structure ($\langle \text{dist1} \rangle = 0$)	40.1	3299.6	90.0	23.8
GGM with Normal error structure ($\langle \text{dist1} \rangle = 0$)	21.1	1191.0	100.0	15.2
RICH with negative binomial error structure ($\langle \text{dist1} \rangle = 0$)	22.6	1037.1	100.0	14.0
Forecast Performance				
SEIUR model with NB error structure ($\langle \text{dist1} \rangle = 0$)	4475.0	46849766.5	10.0	3893.0
GGM with negative binomial error structure ($\langle \text{dist1} \rangle = 0$)	254.6	91255.1	70.0	171.5
RICH with negative binomial error structure ($\langle \text{dist1} \rangle = 0$)	533.4	368516.5	20.0	428.6

Specifying SEIURC

All Data

```

% <=====
% < Author: Gerardo Chowell  =====>
% <=====

function dx=SEIR1(t,x,params0,extra0)

beta0=params0(1);
beta1=params0(2);
alpha=params0(3); % non-homogenous mixing parameter
q1=params0(4);
rho=params0(5);
k=params0(6);
gamma1=params0(7);
N=params0(8);

if t<20

    betaf=beta0;

else

    %betaf=beta0*(1./(t+1)).^q1; % power-law decline
    %betaf=beta0*exp(-q1*t); % exponential decline
    betaf=beta1+(beta0-beta1)*exp(-q1*(t-20)); % exponential decline

end

dx=zeros(6,1); % define the vector of the state derivatives: S, E, I, U, R, C

dx(1,1)= -betaf*x(1,1).*((x(3,1)+x(4,1)).^alpha)./N; %S

dx(2,1)= betaf*x(1,1).*((x(3,1)+x(4,1)).^alpha)./N - k*x(2,1); %E

dx(3,1)= k*rho*x(2,1) - gamma1*x(3,1); %I

dx(4,1)= k*(1-rho)*x(2,1) - gamma1*x(4,1); %U

dx(5,1)= gamma1*(x(3,1)+x(4,1)); %R

dx(6,1)= k*rho*x(2,1); %C

```

$$f(\beta) = \begin{cases} \beta_0, & t < 20 \\ \beta_1 + (\beta_0 - \beta_1)e^{-q_1(t-20)}, & \text{Otherwise} \end{cases}$$

$$\left\{ \begin{array}{l} \dot{S} = -f(\beta)S(t) \frac{I(t) + U(t)^\alpha}{N} \\ \dot{E} = f(\beta)S(t) \frac{I(t) + U(t)^\alpha}{N} - \kappa E(t) \\ \dot{I} = \kappa \rho E(t) - \gamma I(t) \\ \dot{U} = \kappa(1 - \rho)E(t) - \gamma U(t) \\ \dot{R} = \gamma(I(t) + U(t)) \\ \dot{C} = \kappa \rho E(t) \end{array} \right.$$

```

% <===== ODE model =====>
% <===== ODE model =====>
% <===== ODE model =====>

model.fc=@SEIR_unreported_expo_decline; % name of the model function
model.name='SEIR_swiss_covid_underreporting'; % string indicating the name of the ODE model

params.label={'\beta_0','\beta_1','\alpha','q','\rho','\kappa','\gamma','N'}; % list of symbols to refer to the model parameters
params.LB=[0.001 0.5 0 0.01 0.01 0.01 47332614]; % lower bound values of the parameter estimates
params.UB=[5 2 1 10 1 1 1 47332614]; % upper bound values of the parameter estimates
params.initial=[0.6 0.01 1 0.01 1 1/5 1/4 47332614]; % initial parameter values/guesses
params.fixed=[0 0 1 0 0 1 1 1]; % Boolean vector to indicate any parameters that should remain fixed (1) to initial values indicated in params.
params.fixI0=1; % Boolean variable indicating if the initial value of the fitting variable is fixed according to the first observation in the t
params.composite=@R0s_unreported; % Estimate a composite function of the individual model parameter estimates otherwise it is left empty.
params.composite_name='R0s_unreported'; % Name of the composite parameter
params.extra0='';

vars.label={'S','E','I','U','R','C'}; % list of symbols to refer to the variables included in the model
vars.initial=[params.initial(8)-1 0 1 0 0 1]; % vector of initial conditions for the model variables
vars.fit_index=6; % index of the model's variable that will be fit to the observed time series data
vars.fit_diff=1; % boolean variable to indicate if the derivative of model's fitting variable should be fit to data.

```

Preparing options_fit.m

Fitting using all data

```
% <===== Parameters of the rolling window analysis =====>
% <===== Parameters of the rolling window analysis =====>
% <===== Parameters of the rolling window analysis =====>

windowsize1=109; % moving window size

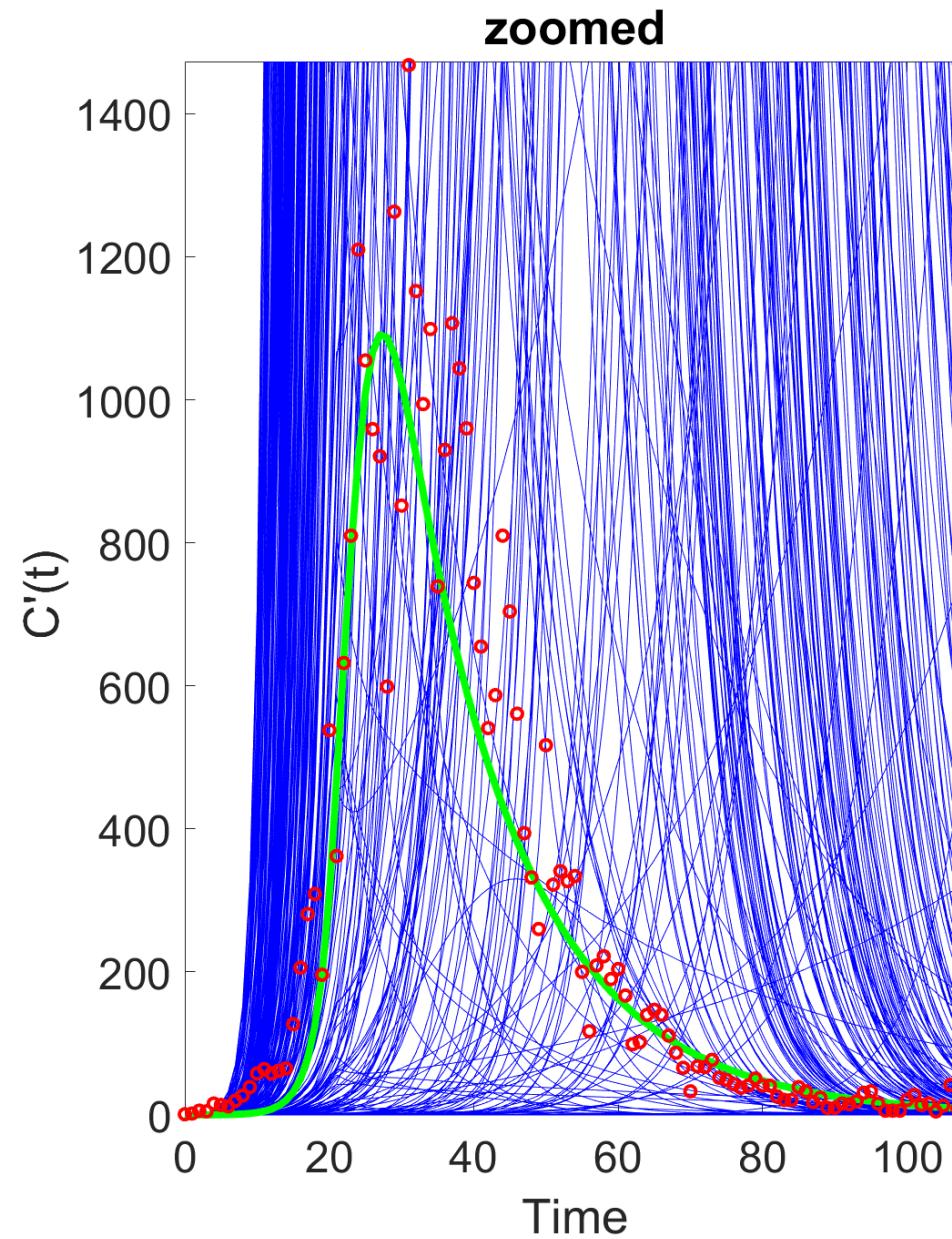
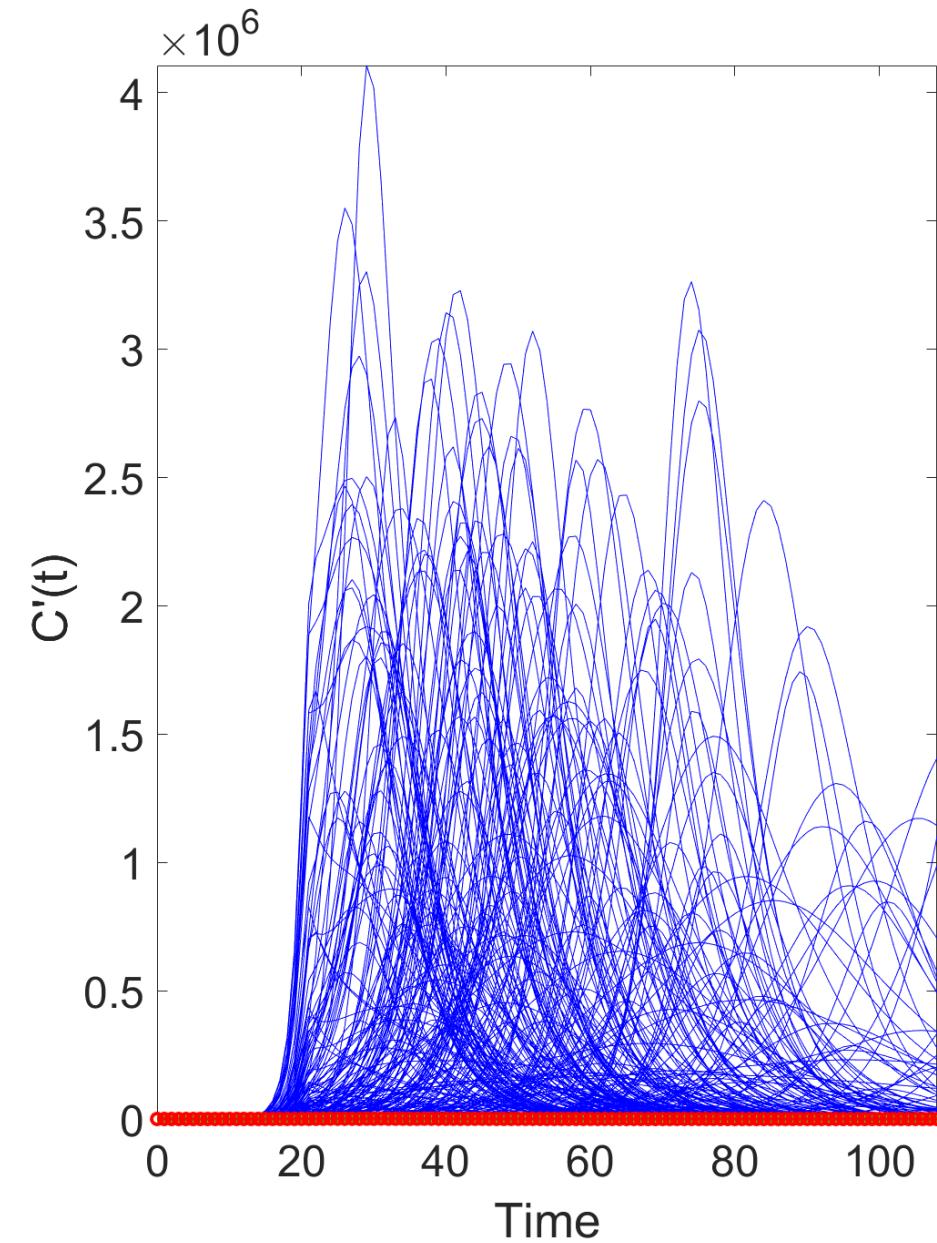
tstart1=1; % time point for the start of rolling window analysis

tend1=1; %time point for the end of the rolling window analysis

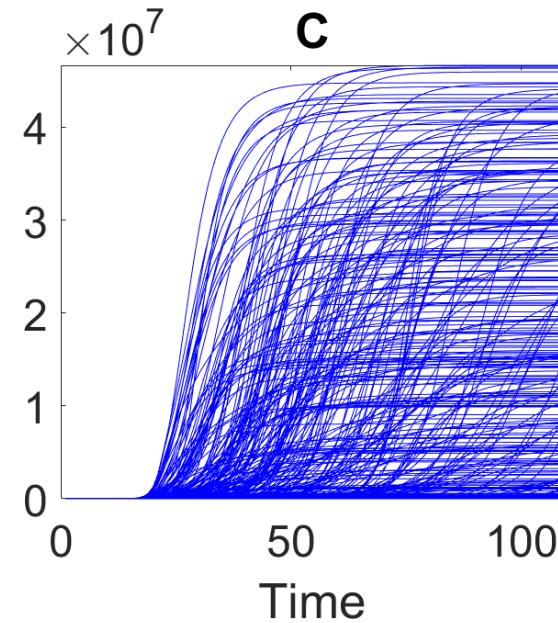
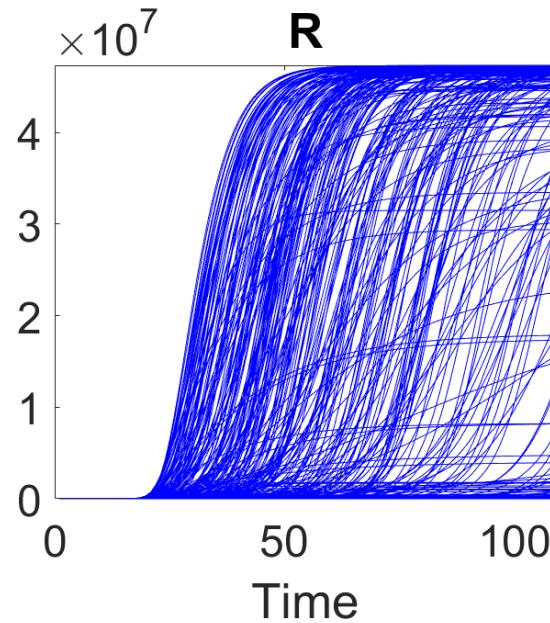
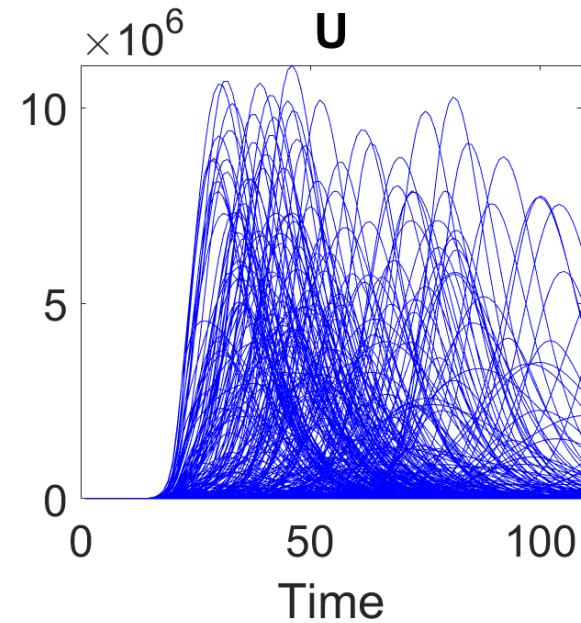
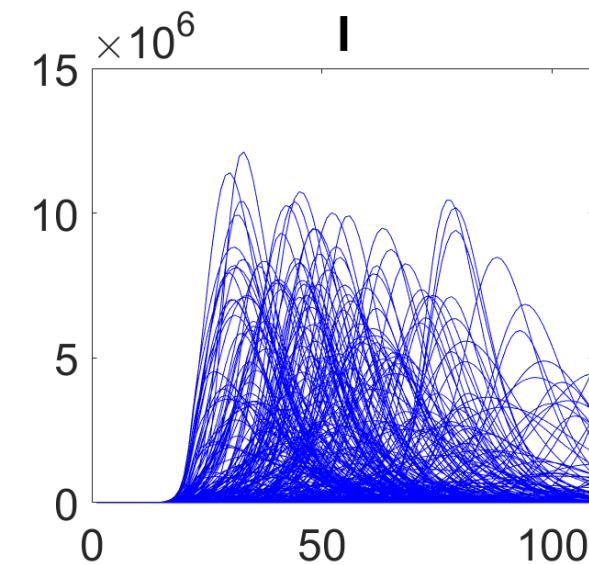
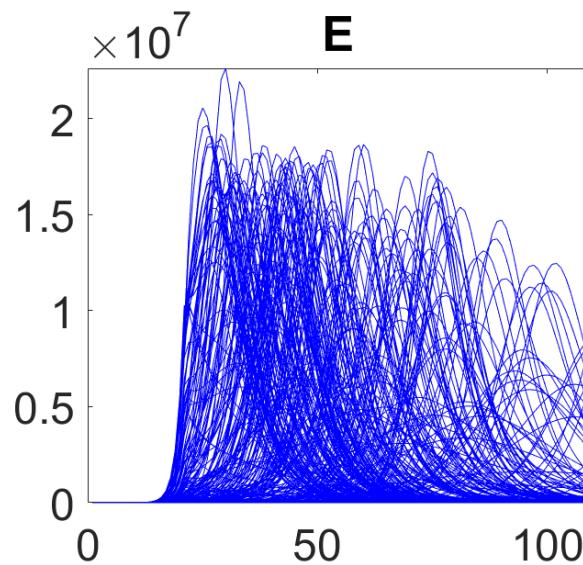
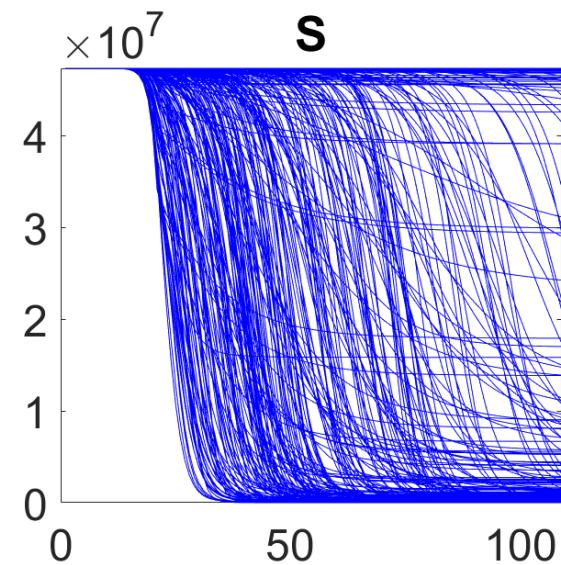
printscreen1=1;
```

Generating preliminary model solutions

```
plotODEModel(@options_fit_SEIR_unreported_covid_swiss_dist1_0)
```



Estimated α

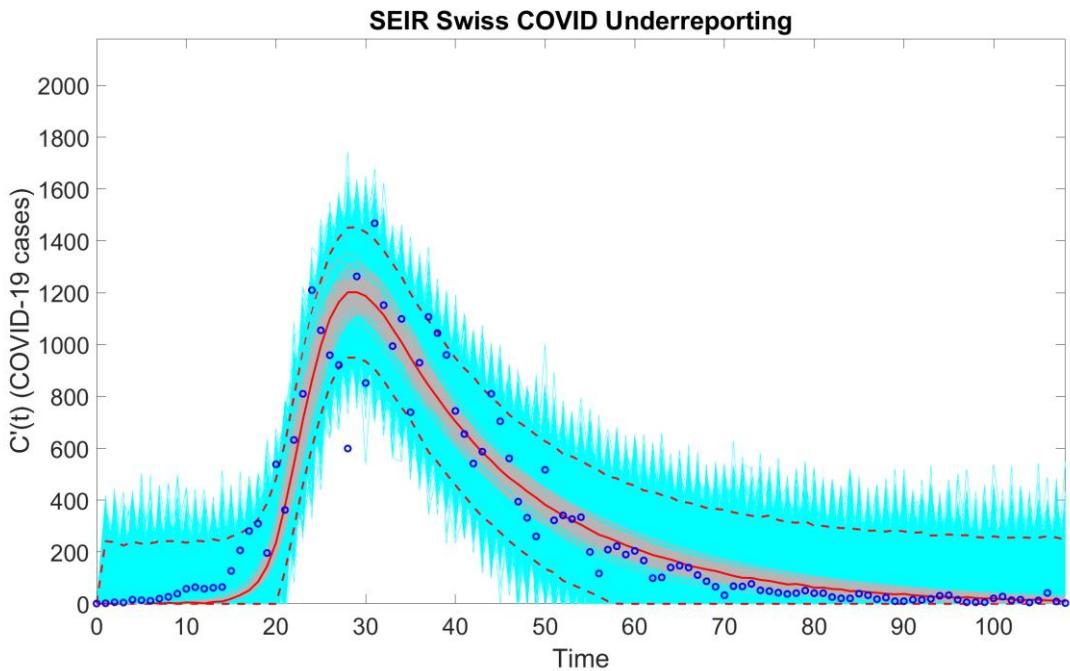


Estimated α

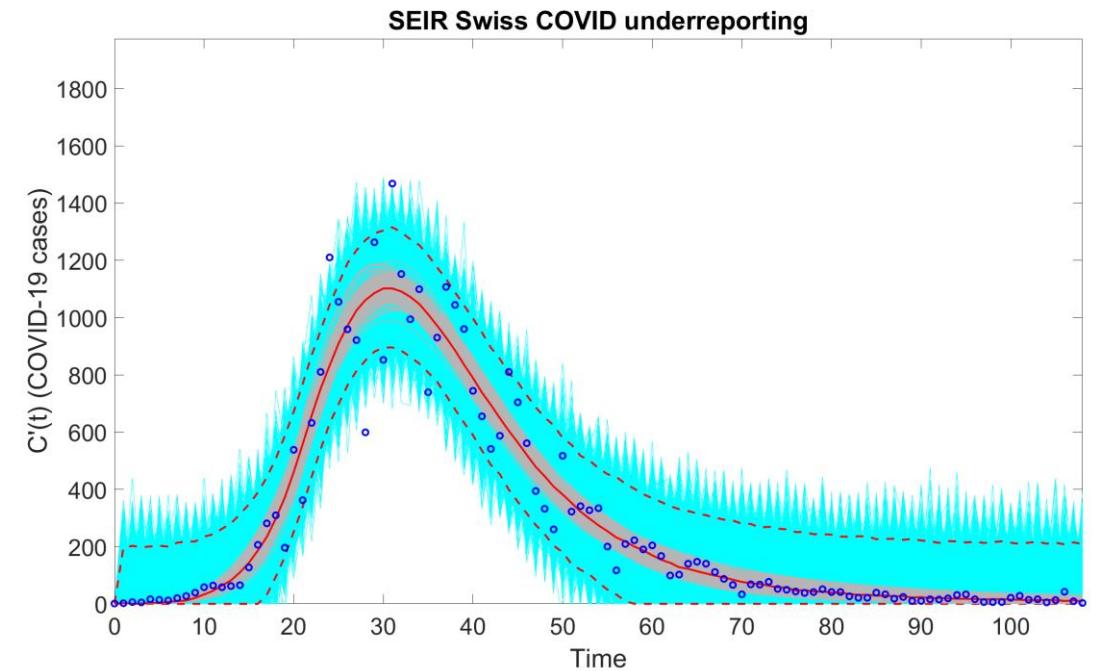
Fitting, plotting, and evaluating the model with quantified uncertainty

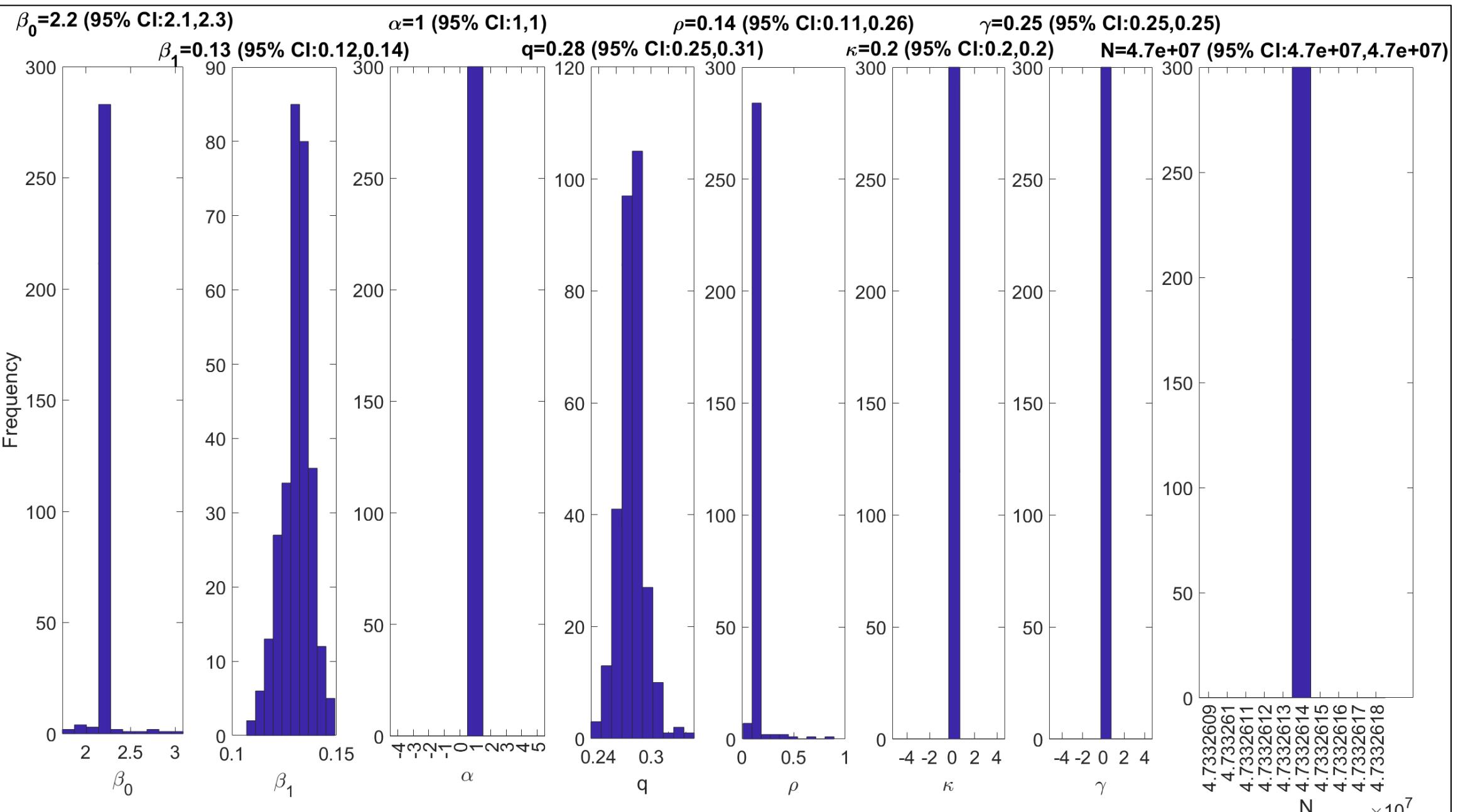
```
(1) Run_Fit_ODEModel(@options_fit_SEIR_unreported_covid_swiss_dist1_0  
, 1, 1, 109)  
(2) plotForecast_ODEModel(@options_fit_SEIR_unreported_covid_swiss_di  
st1_0, 1, 1, 109)
```

Fixed α

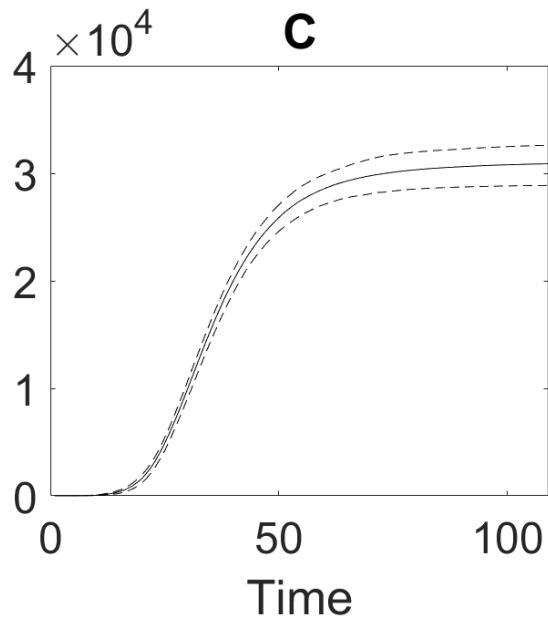
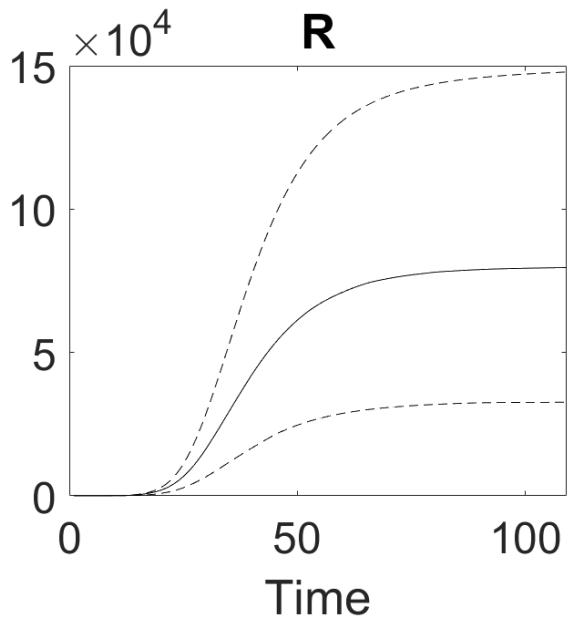
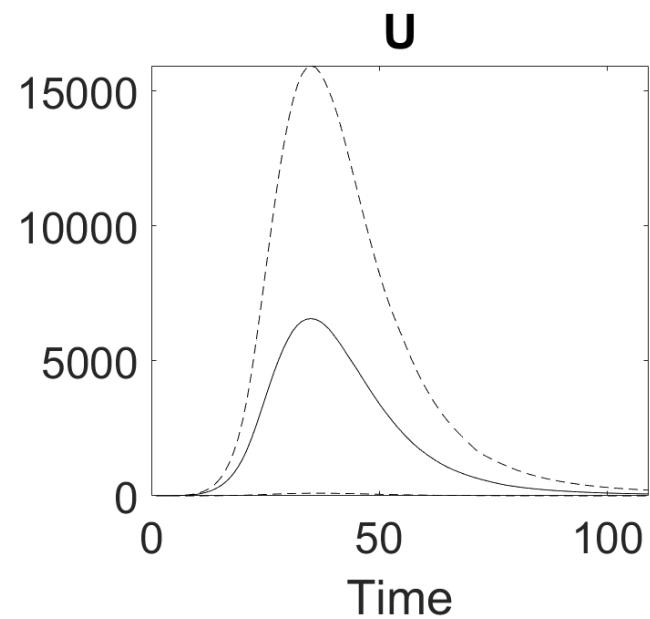
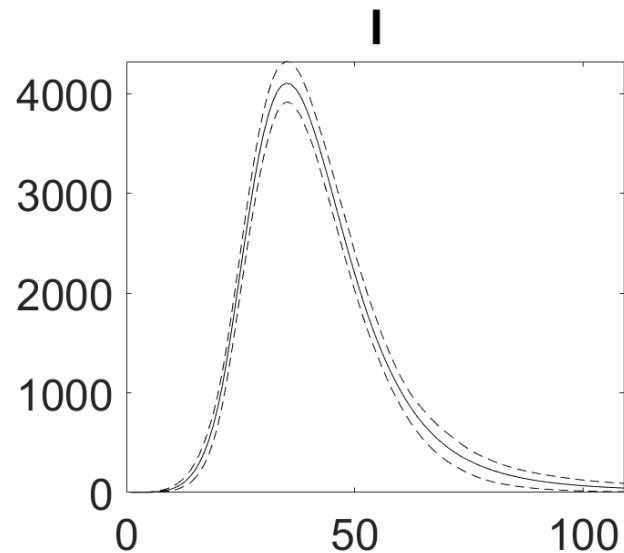
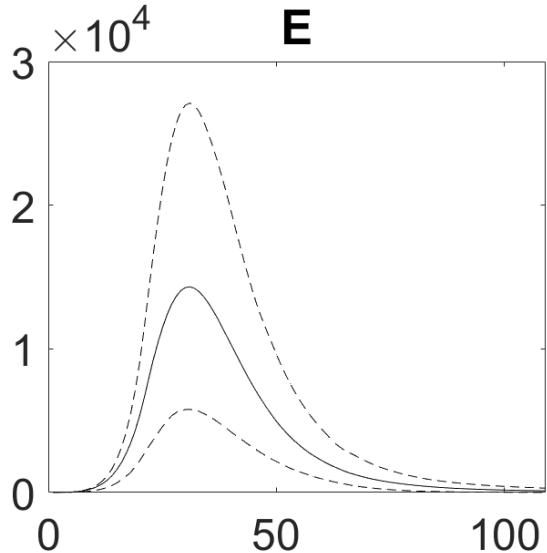
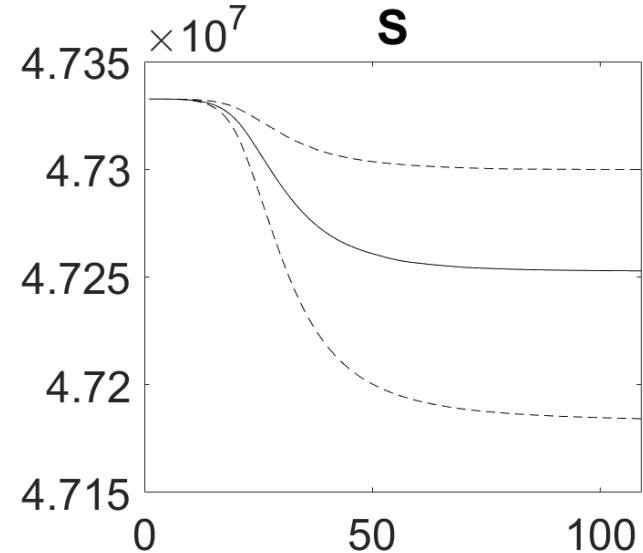


Estimated α





Estimated α

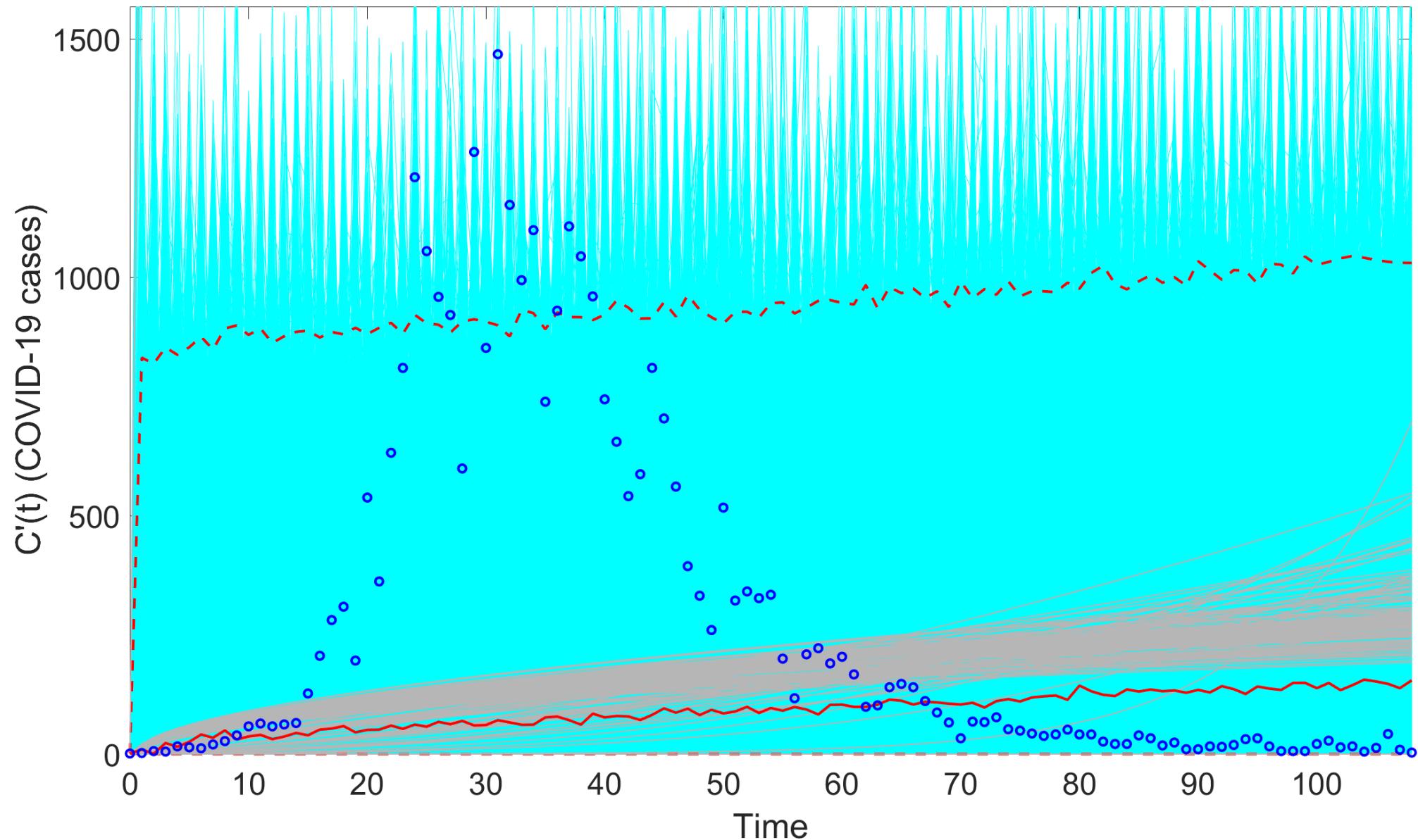


Estimated α

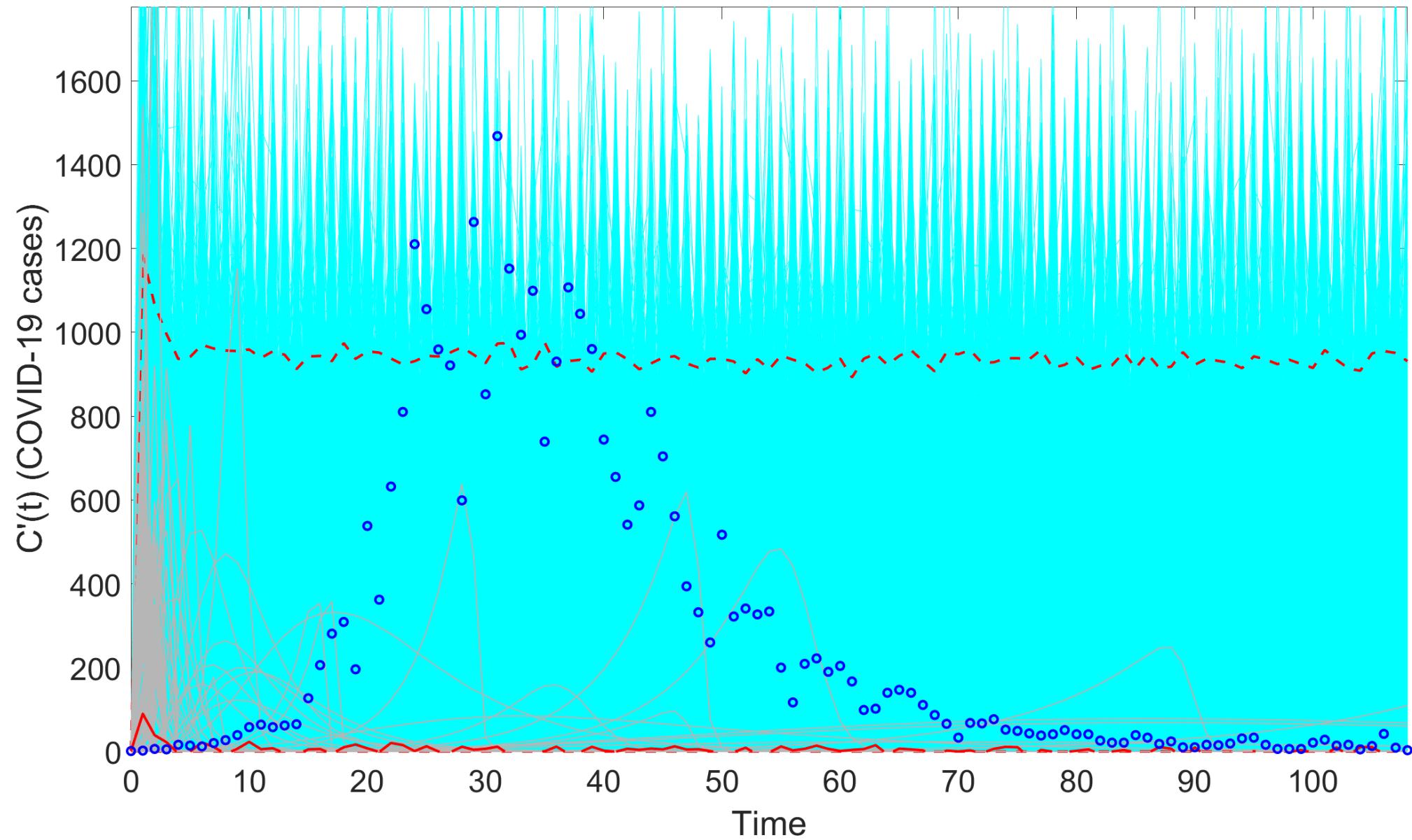
Model Comparison (All Data)

SEIUR Normal, GGM Normal & RICH Normal

GGM model



RICH model



Model	MAE	MSE	Coverage 95% PI	WIS
Calibration Performance				
SEIUR model with NLSQ/ Normal error structure ($\langle \text{dist1} \rangle = 0$)	67.2	13189.4	92.7	48.3
GGM with Normal error structure ($\langle \text{dist1} \rangle = 0$)	297.6	197605.8	88.1	176.6
RICH with negative binomial error structure ($\langle \text{dist1} \rangle = 0$)	284.3	216949.7	89.0	173.1