

# Forecasting Black Sigatoka Infection Risks with Latent Neural ODEs

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**Black  
Sigatoka**





Applying fungicides regularly  
accounts for

**40%**

of the banana production cost



Forecast black  
Sigatoka infections  
risks

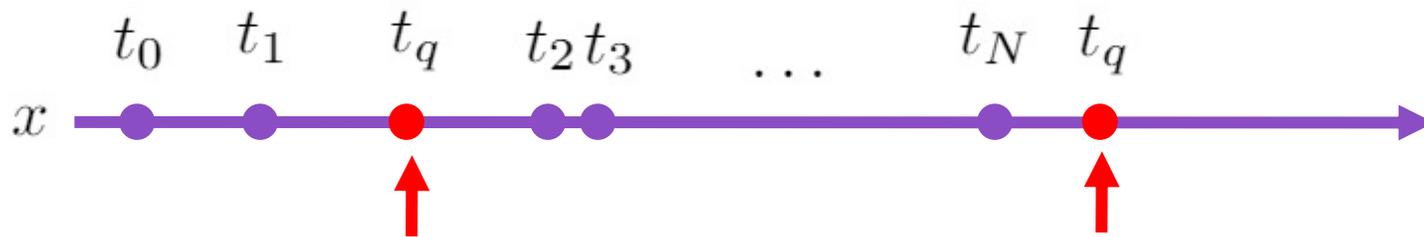
**1 month**

into the future

**Bonus:**  
Outstanding interpolation  
capabilities, even when  
inferencing with **10%** of  
data window!

**Multiple predictor  
Neural ODE  
(MR. NODE)**





$x$ : Infection rate  
 $t_0, \dots, t_N$ : Observed time steps (possibly irregular)  
 $t_q$ : Unobserved time step ( $t_q \geq t_0$ )  
 $w$ : Weather conditions

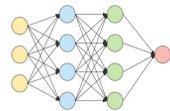
**Goal: Find infection rate at time  $t_q$  using weather!!**

Using MR. NODE:

$x_{t_0}, \dots, x_{t_N}, w_{t_0}, \dots, w_{t_N}$

Encoder RNN

$z_{t_0}$



$\frac{dz}{dt}$

$t_q$

Some values of  $z$  before  $t_q$

Latent space

$$z_{t_q} = z_{t_0} + \int_{t_0}^{t_q} \frac{dz}{dt} dt$$

$z_{t_q}$

Decoder

~~$\hat{x}_{t_q}$~~

**(1)**



**(2)**

**Innovations:**  
**(1) 'Partial' autoencoder**  
**(2) Inject weather into  $dz/dt$**

# Datasets



# Data generation

Bebber (2019)

$$r(T) = \left( \frac{T_{max} - T}{T_{max} - T_{opt}} \right) \left( \frac{T - T_{min}}{T_{opt} - T_{min}} \right)^{\frac{T_{opt} - T_{min}}{T_{max} - T_{opt}}}$$

$$H(t, T) = r(T) \left( \frac{t}{\alpha} \right)^\gamma$$

$$F(t, T) = 1 - e^{-H(t, T)}$$

$$Y(t, T) = \beta F(t, T)$$



relative humidity



canopy temperature



moisture storage on canopy

(N = 91,556)



Relative number of infections

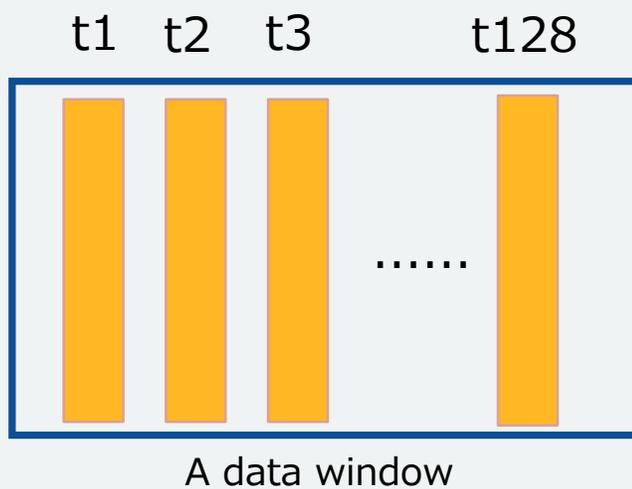
# Experiments



- Encoder: LSTM
- Loss Functions:
  - Negative Log Likelihood (train & valid)
  - Mean Squared Error (test)

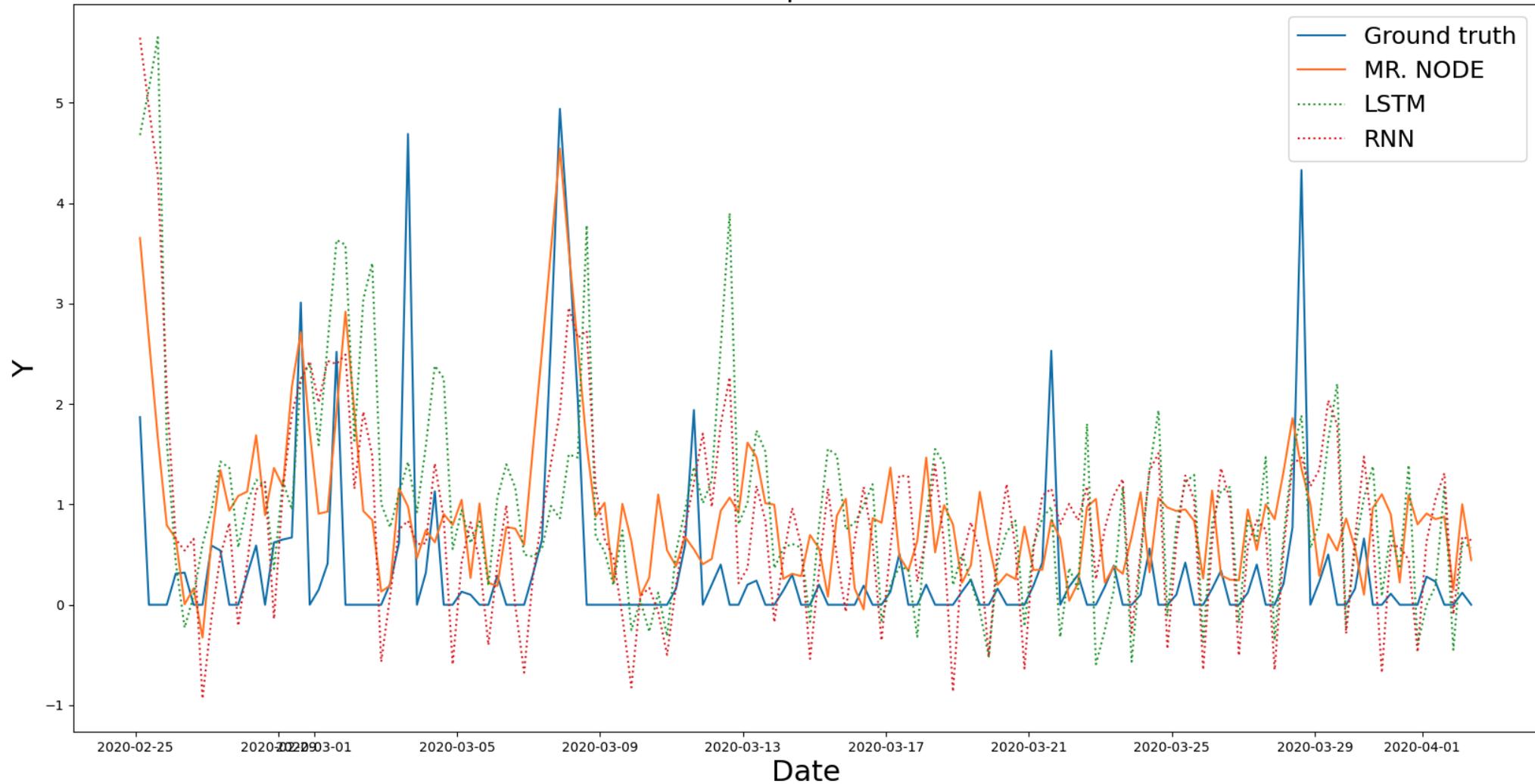
# Long Extrapolation

	# encoded	#reconstructed	#extrapolated
Training	128	128	0
Validation	100	100	150
Extrapolation Test	100/70/50/30 (drop rate 0/0.3/0.5/0.7)	-	150 (37.5 days)
Interpolation Test	100/70/30/10 (drop rate 0/0.3/0.7/0.9)	100	0



# Long Extrapolation

Ground truth Y vs extrapolations for the 3 models

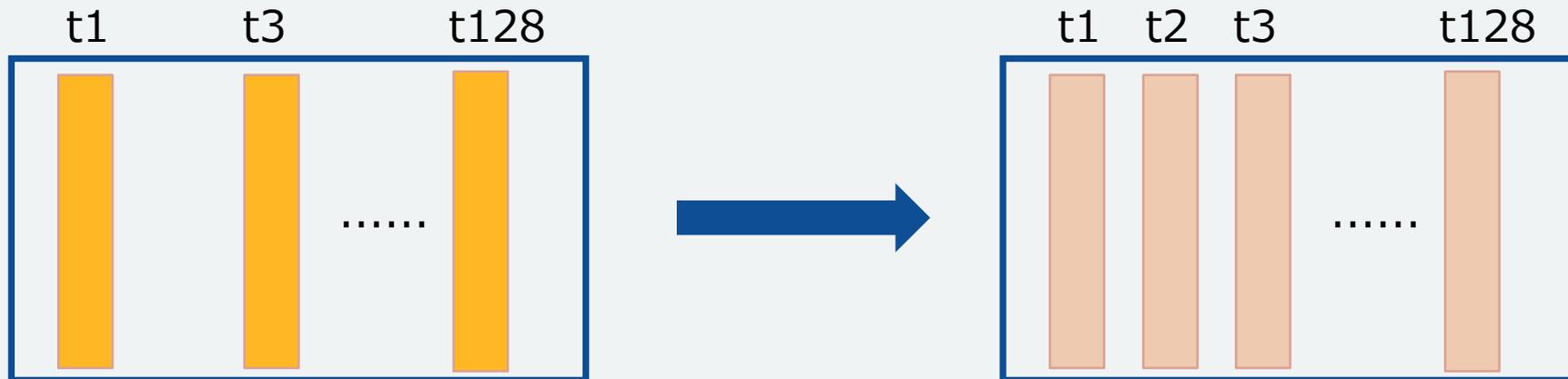


# Long Extrapolation

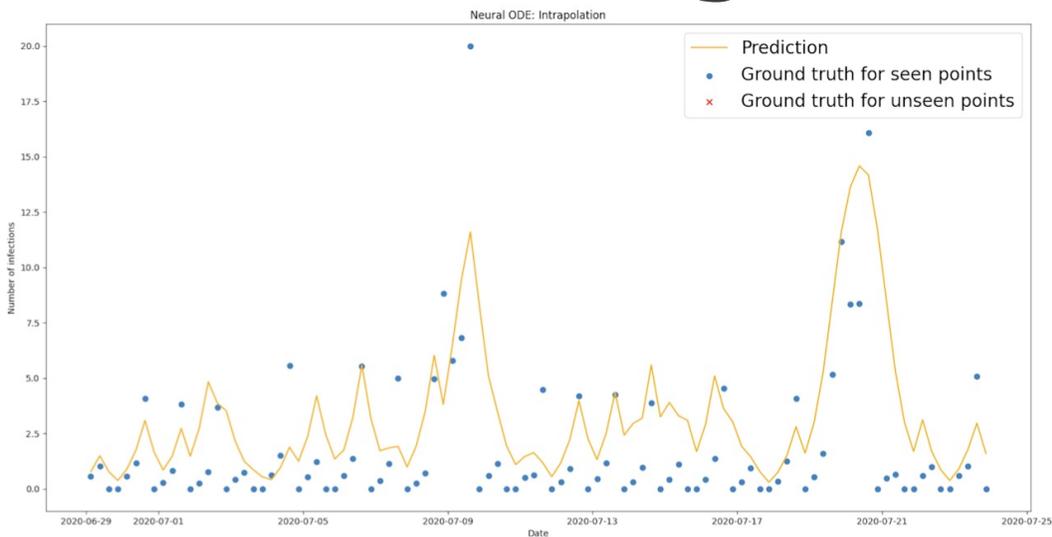
Method	Drop rates	MSE on test set
RNN	0	13.55
	0.3	13.51
	0.5	12.62
	0.7	13.70
LSTM	0	12.76
	0.3	12.71
	0.5	17.94
	0.7	14.12
MR. NODE	0	<b>12.16</b>
	0.3	<b>12.29</b>
	0.5	<b>12.40</b>
	0.7	<b>12.68</b>

# Irregular Interpolation

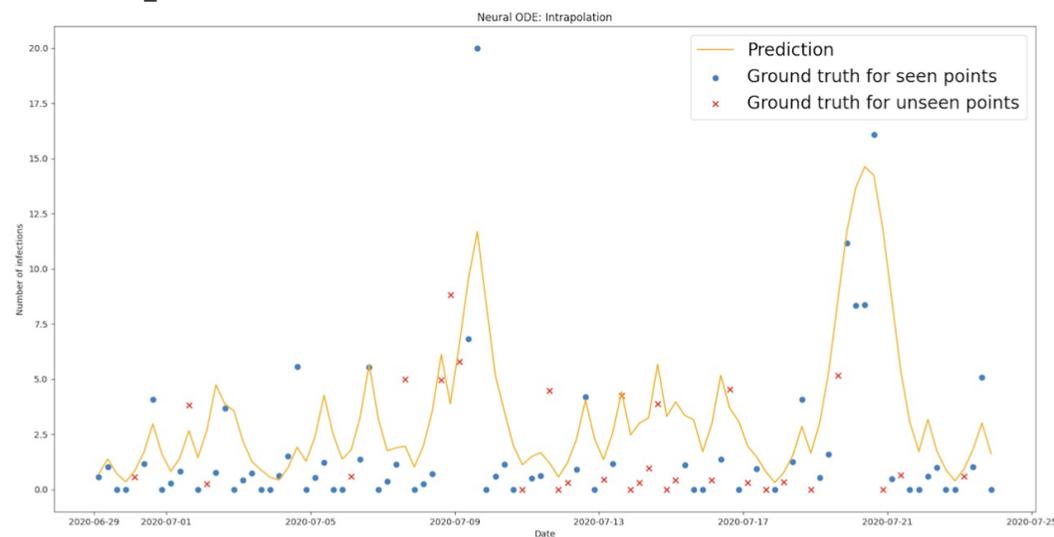
	# encoded	#reconstructed	#extrapolated
Training	128	128	0
Validation	100	100	150
Extrapolation Test	100/70/50/30 (drop rate 0/0.3/0.5/0.7)	-	150 (37.5 days)
Interpolation Test	100/70/30/10 (drop rate 0/0.3/0.7/0.9)	100	0



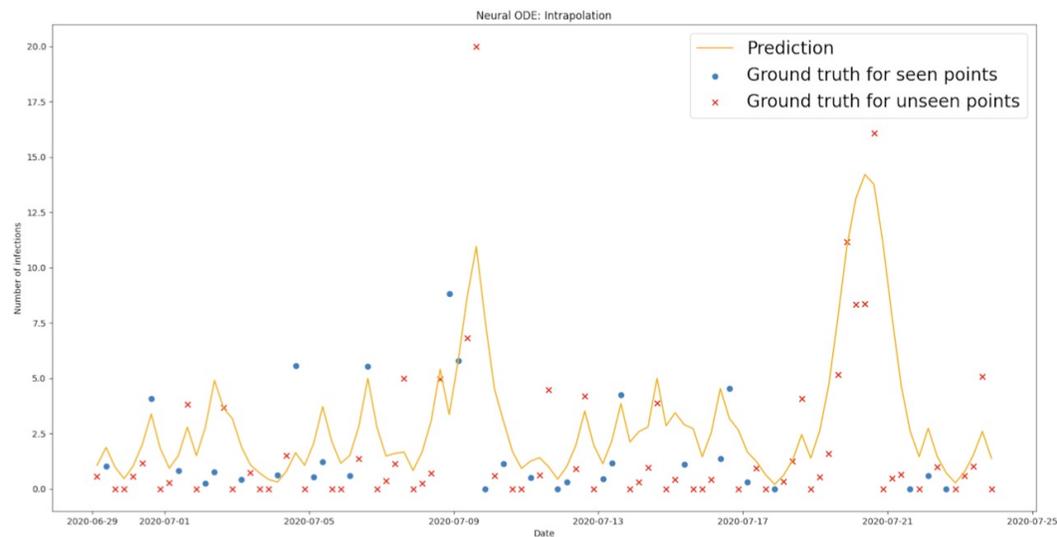
# Irregular Interpolation



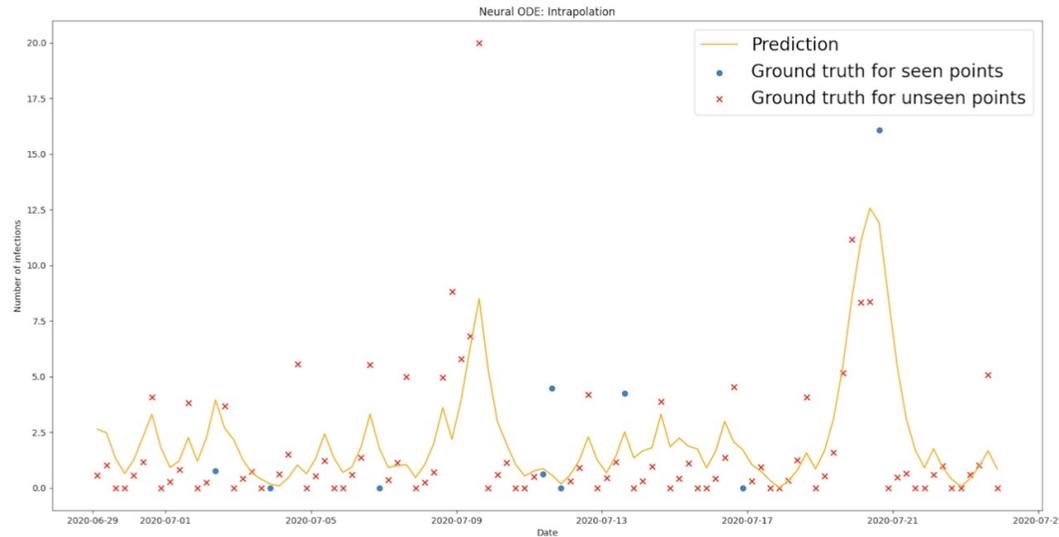
(a) dropping rate = 0



(b) dropping rate = 0.3



(c) dropping rate = 0.7



(d) dropping rate = 0.9

## Takeaway

- New ML method for time-series with multiple predictors
- Can predict **1 month** into the future
- Outstanding interpolation capabilities, even when using **only 10%** of the data window

**Thank you!** 😊

