Longitudinal analysis of Shigella

0.1 Data description

• Step 1: Load the Dataset

• Step 2: Get a Quick Overview of the Data Structure

Table 1: Data summary

Name	df
Number of rows	2374
Number of columns	31
Column type frequency:	
character	9
numeric	22
Group variables	None

Variable type: character

skim_variable	n_missing	complete_rate	min	max	empty	n_unique	whitespace
isotype_name	0	1.00	3	3	0	2	0
dilution_name	0	1.00	6	6	0	1	0
$study_name$	0	1.00	4	22	0	5	0
sampleID	0	1.00	6	11	0	1017	0
sid	0	1.00	6	11	0	1017	0
unq_id	0	1.00	22	27	0	2374	0
$cohort_name$	0	1.00	3	11	0	12	0

skim_variable	n_missing	complete_rate	min	max	empty	n_unique	whitespace
site_name	0	1.00	5	12	0	5	0
treatment	1126	0.53	7	7	0	2	0

Variable type: numeric

skim_variable n_	_missi	ngomplete_	_r ante an	sd	p0	p25	p50	p75	p100	hist
isotype	0	1.00	1.50	0.50	1.00	1.00	1.50	2.00	2.00	
dilution	0	1.00	1.00	0.00	1.00	1.00	1.00	1.00	1.00	
cohort	0	1.00	8.49	1.66	4.00	9.00	9.00	9.00	15.00	
site	0	1.00	5.33	2.22	1.00	2.50	7.00	7.00	7.00	
age	0	1.00	6.58	8.66	0.08	2.00	3.67	7.00	50.00	
timepoint	0	1.00	969.01	901.92	0.00	0.00	1825.0	01825.00	1825.00	
Actual day	1942	0.18	53.06	62.90	2.00	7.00	30.00	90.00	204.00	
$ipab_MFI$	0	1.00	43525.8	3459594.9		818.58	34759.9	286098.8	1189355.	75
					1.25					
sf3aospbsa_MFl	0	1.00	3651.27	8563.89		183.25	753.71	2956.48	83828.9	2
					9.00					
sf2aospbsa_MFl	0	1.00	4681.13	3 14202.9		100.06	489.04	2694.00	214007.	67
					12.00					
sf6ospbsa_MFI	0	1.00	4043.35	5 9996.03		278.25	$5\ 1036.29$	93714.58	166878.	50
					7.75					
sonneiospbsa_M	FI 0	1.00	3007.76	$5\ 12898.1$		28.08	118.12	887.46	184109.	50
					14.50					
n_ipab_MFI	0	1.00	24971.0	834729.7		361.53	3 1903.4	751093.8	5116048.	97
					0.63					
$n_sf3aospbsa_N$	IFI0	1.00	5702.38	$3\ 12801.3$		320.15	$5\ 1273.0$	04743.07	112888.	86
					12.10					
$n_sf2aospbsa_N$	1F10	1.00	5308.11	15272.9		135.66	621.84	3295.17	222195.	19
					11.82					
n_sf6ospbsa_M	F1 0	1.00	2991.34	1 6997.96		231.92	2 845.01	2826.64	108831.	02
	3.657	4.00	0-1-0		6.84		100.00	1005.15	210021	
n_sonneiospbsa_	_M 0 1	1.00	3747.64	14652.8		38.78	183.09	1335.17	219024.	17
		4.00		20.40	28.75			01.00	200.00	
ipab_BC	0	1.00	80.03	29.48	17.00	59.00	73.00	91.00	260.00	
sf3aospbsa_BC	0	1.00	103.91	22.52	57.00	88.00	100.00		226.00	
sf2aospbsa_BC	0	1.00	67.03	18.96	23.00	54.00	63.00	76.00	155.00	
sf6ospbsa_BC	0	1.00	56.18	13.04	27.00	47.00	53.00	63.00	115.00	
sonneiospbsa_B	C 0	1.00	58.37	14.60	17.00	49.00	58.00	68.00	114.00	

 $\bullet\,$ Step 3: Identify and Summarize Missing Values (for the entire dataset and the SOSAR study)

A tibble: 31 x 2

	variable	missing_count
	<chr></chr>	<int></int>
1	Actual day	1942
2	treatment	1126
3	isotype	0
4	isotype_name	0
5	dilution	0
6	${\tt dilution_name}$	0
7	study_name	0
8	sampleID	0
9	sid	0
10	unq_id	0
# -	i 21 more rows	

A tibble: 31×2

	variable	missing_count
	<chr></chr>	<int></int>
1	treatment	436
2	Actual day	4
3	isotype	0
4	isotype_name	0
5	dilution	0
6	dilution_name	0
7	study_name	0
8	sampleID	0
9	sid	0
10	unq_id	0
# :	i 21 more rows	

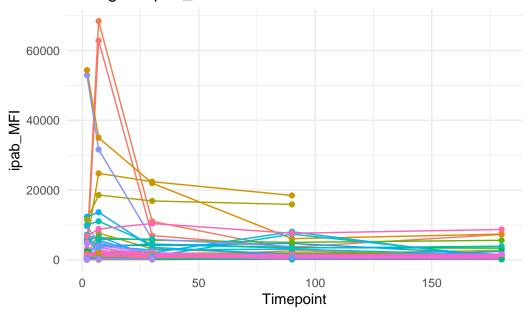
0.2 Exploratory Data Analysis

• Step 4: Filter Data for the SOSAR Study and Split Data by Isotype

Verifying the unique sample identification numbers (SIDs) is crucial. There are 48 SIDs in this SOSAR study.

• Step 5: Plot Quantitative Response Change Over Time

Change in ipab_MFI Over Time



0.3 Longitudinal Antibody Decay Modeling

- Step 6: Prepare Data for JAGS Model
- Step 7: Subset Data for Model Testing

```
#subset data for checking
dL_sub <- dL %>%
filter(index_id %in% sample(unique(index_id), 20))
```

- Step 8: Prepare Data and Priors for JAGS
- Step 9: Run the JAGS Model

```
dump_and_quit <- function() {
  dump.frames(to.file = TRUE)
  q(status = 1)
}
options(error = dump_and_quit)</pre>
```

[1] "Starting run.jags execution"

```
List of 5
           : num [1:21, 1:5] 2 2 2 2 2 2 2 2 2 2 ...
 $ smpl.t
  ..- attr(*, "dimnames")=List of 2
  ....$ subjects : chr [1:21] "SOSAR-11001" "SOSAR-12017" "SOSAR-11012" "SOSAR-12005" ...
  ....$ visit number: chr [1:5] "V1" "V2" "V3" "V4" ...
                : num [1:21, 1:5, 1:2] -4.61 -4.61 -4.61 -4.61 -4.61 ...
  ..- attr(*, "dimnames")=List of 3
  ....$ subjects : chr [1:21] "SOSAR-11001" "SOSAR-12017" "SOSAR-11012" "SOSAR-12005" ...
  ....$ visit_number: chr [1:5] "V1" "V2" "V3" "V4" ...
  ....$ antigens : chr [1:2] "IgG" "IgA"
 $ n_antigen_isos: int 2
 $ nsmpl
           : num [1:21] 5 4 5 5 5 5 5 5 5 5 ...
 $ nsubj
                : num 21
 - attr(*, "antigens")= chr [1:2] "IgG" "IgA"
 - attr(*, "n_antigens")= int 2
 - attr(*, "ids")= chr [1:21] "SOSAR-11001" "SOSAR-12017" "SOSAR-11012" "SOSAR-12005" ...
NULL
List of 6
 $ n_params : num 5
 $ mu.hyp
              : num [1:2, 1:5] 1 1 7 7 1 1 -4 -4 -1 -1
 $ prec.hyp : num [1:2, 1:5, 1:5] 1 1 0 0 0 0 0 0 0 0 ...
 $ omega
              : num [1:2, 1:5, 1:5] 1 1 0 0 0 0 0 0 0 0 ...
             : num [1:2] 20 20
 $ wishdf
 $ prec.logy.hyp: num [1:2, 1:2] 4 4 1 1
NULL
Calling 4 simulations using the parallel method...
Following the progress of chain 1 (the program will wait for all chains
to finish before continuing):
Welcome to JAGS 4.3.2 on Wed Aug 28 00:47:59 2024
JAGS is free software and comes with ABSOLUTELY NO WARRANTY
Loading module: basemod: ok
Loading module: bugs: ok
. . Reading data file data.txt
. Compiling model graph
   Resolving undeclared variables
   Allocating nodes
Graph information:
   Observed stochastic nodes: 186
   Unobserved stochastic nodes: 54
   Total graph size: 3201
```

- . Reading parameter file inits1.txt
- . Initializing model
- . Adapting 100

. Updating 100

. . . . Updating $\mathbf{0}$

. Deleting model

•

All chains have finished

Warning: The adaptation phase of one or more models was not completed in 100 iterations, so the current samples may not be optimal - try increasing the number of iterations to the "adapt" argument

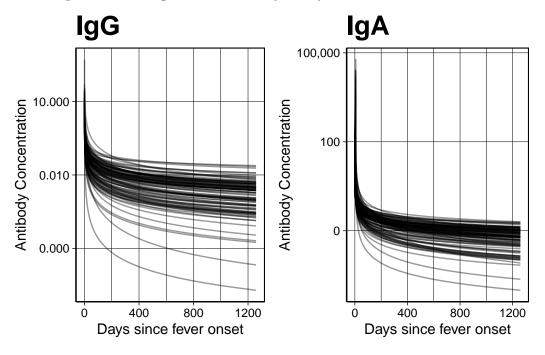
Simulation complete. Reading coda files... Coda files loaded successfully Finished running the simulation

- [1] "run.jags completed successfully"
 - Step 10: Covert JAGS Output to MCMC List

```
mcmc_list <- as.mcmc.list(jags.post)
mcmc_df <- ggs(mcmc_list)</pre>
```

• Step 11: Prepare Data for Serocalculator Package

• Step 12: Plot Longitudinal Antibody Decay



• Step 13: Define the Antibody Calculation Function

```
ab <- function(t, y0, y1, t1, alpha, shape) {
  beta <- log(y1/y0) / t1
  if (t <= t1) {
    yt <- y0 * exp(beta * t)
  } else {
    yt <- (y1^(1 - shape) - (1 - shape) * alpha * (t - t1))^(1 / (1 - shape))
  }
  return(yt)
}</pre>
```

- Step 14: Generate Time Points for Antibody Levels
- Step 15: Calculate Antibody Levels Over Time

• Step 16: Summarize and Plot Antibody Decay Data

Longitudinal Antibody Decay with Uncertainty Intervals

