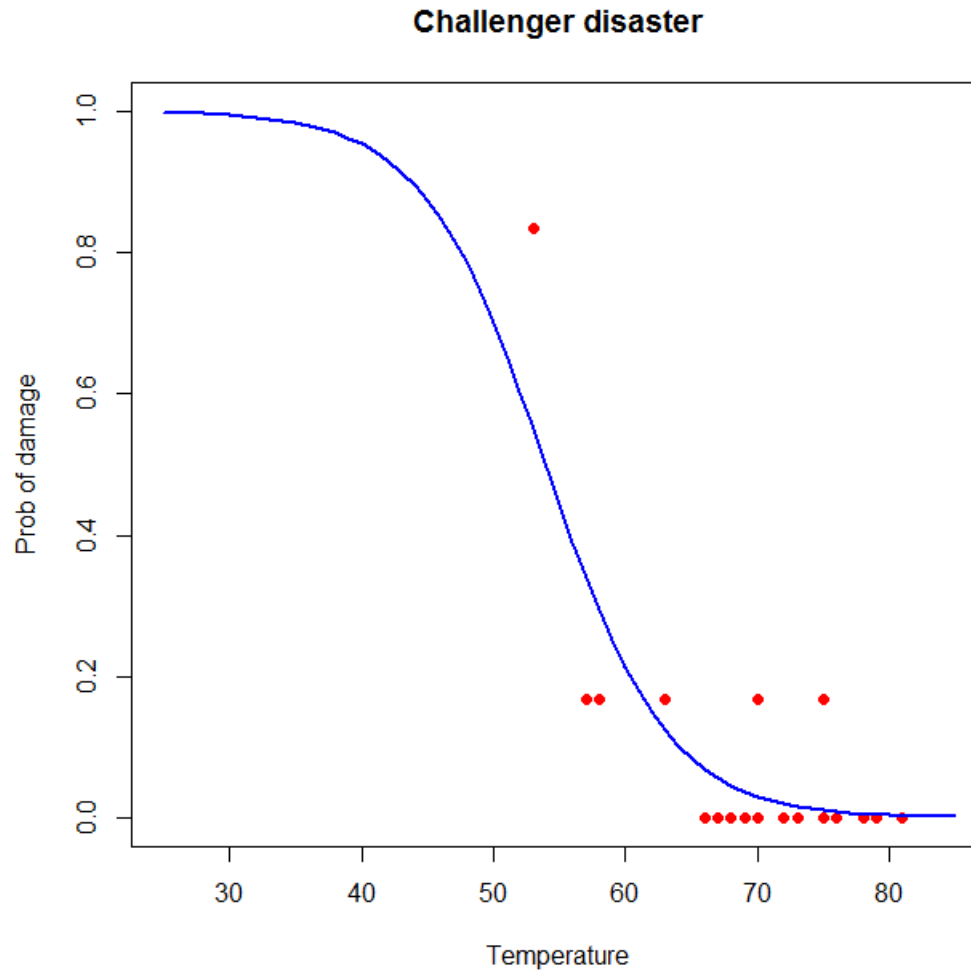


# Generalized linear modeling with



Source: Faraway (2006).



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# Why not linear regression?

- 0/1 data (activity, infection, presence, sex)
- proportional data (0 – 100 %)
- number of successes vs. number of failures
- count data (species richness)



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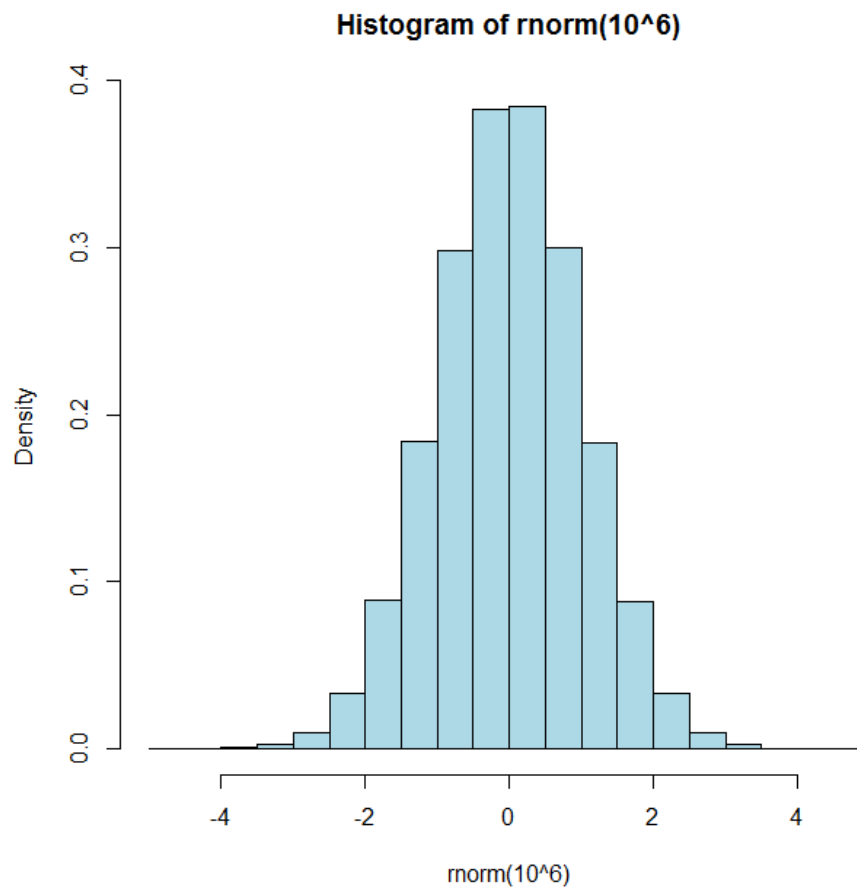
# Before getting started, we should think about

1. distribution of the **response**
2. systematic part (covariates)
3. link-function between expected value of the response and the systematic part



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# Normal distribution

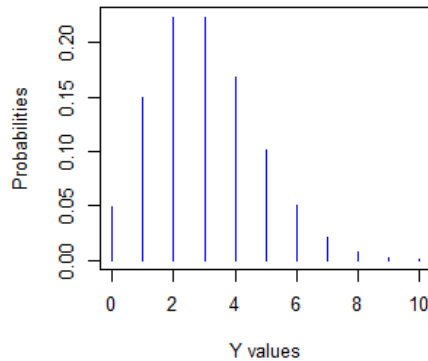


$$f(y_i; \mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} * e^{-\frac{(y_i - \mu)^2}{2\sigma^2}}$$

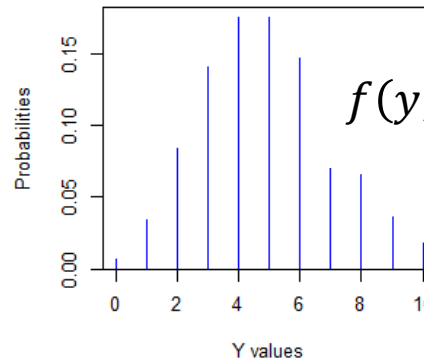
defined by mean  
and standard deviation

# Poisson distribution

Poisson with mean 3



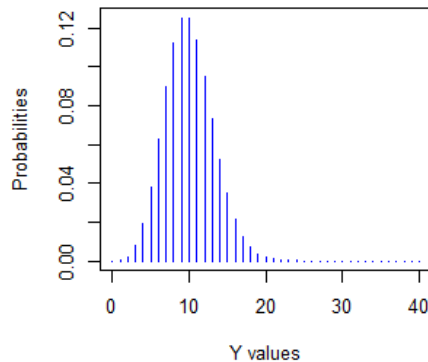
Poisson with mean 5



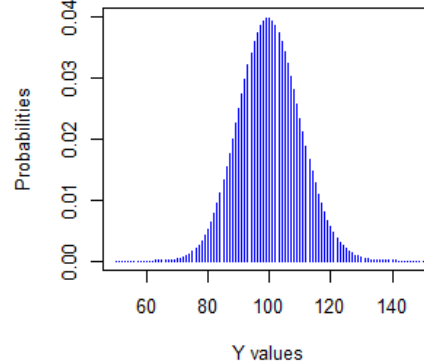
$$f(y; \mu) = \frac{\mu^y * e^{-\mu}}{y!} \quad y \geq 0, y \text{ integer}$$

mean = variance

Poisson with mean 10



Poisson with mean 100



-> larger mean values have also a larger variance

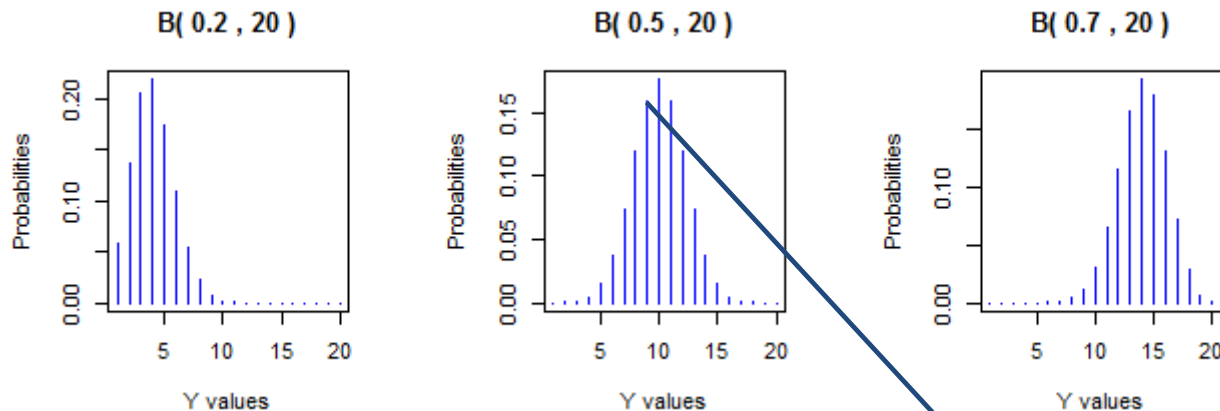
**overdispersion:** if the variance is larger than the mean

Modified after: Zuur et al. (2009).

# Bernoulli and binomial distribution

- Tossing a coin (head or tail)
- Bernoulli distribution = binomial distribution with  $N = 1$

$$f(y; \pi) = \binom{N}{y} * \pi^y * (1 - \pi)^{N-y}$$



Modified after: Zuur et al. (2009).

$$(20!/(9! * 11!)) * 0.5^9 * (1-0.5)^{11} = 0.16$$



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# Further common distributions

1. **Negative binomial distribution** -> quick and dirty solution for overdispersion
2. **Gamma distribution** -> can be used for a continuous response variable that has positive values ( $> 0$ )

# Predictor function



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$$g(x_i) = \alpha + \beta_1 X_{1i} + \dots + \beta_n X_{ni}$$





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# Poisson predictor function

1. distribution -> increase in spread
2. density curves avoid negative realizations
3. exponential link -> no negative fitted values
4. Maximum likelihood algorithm (see Zuur 2009: 213)

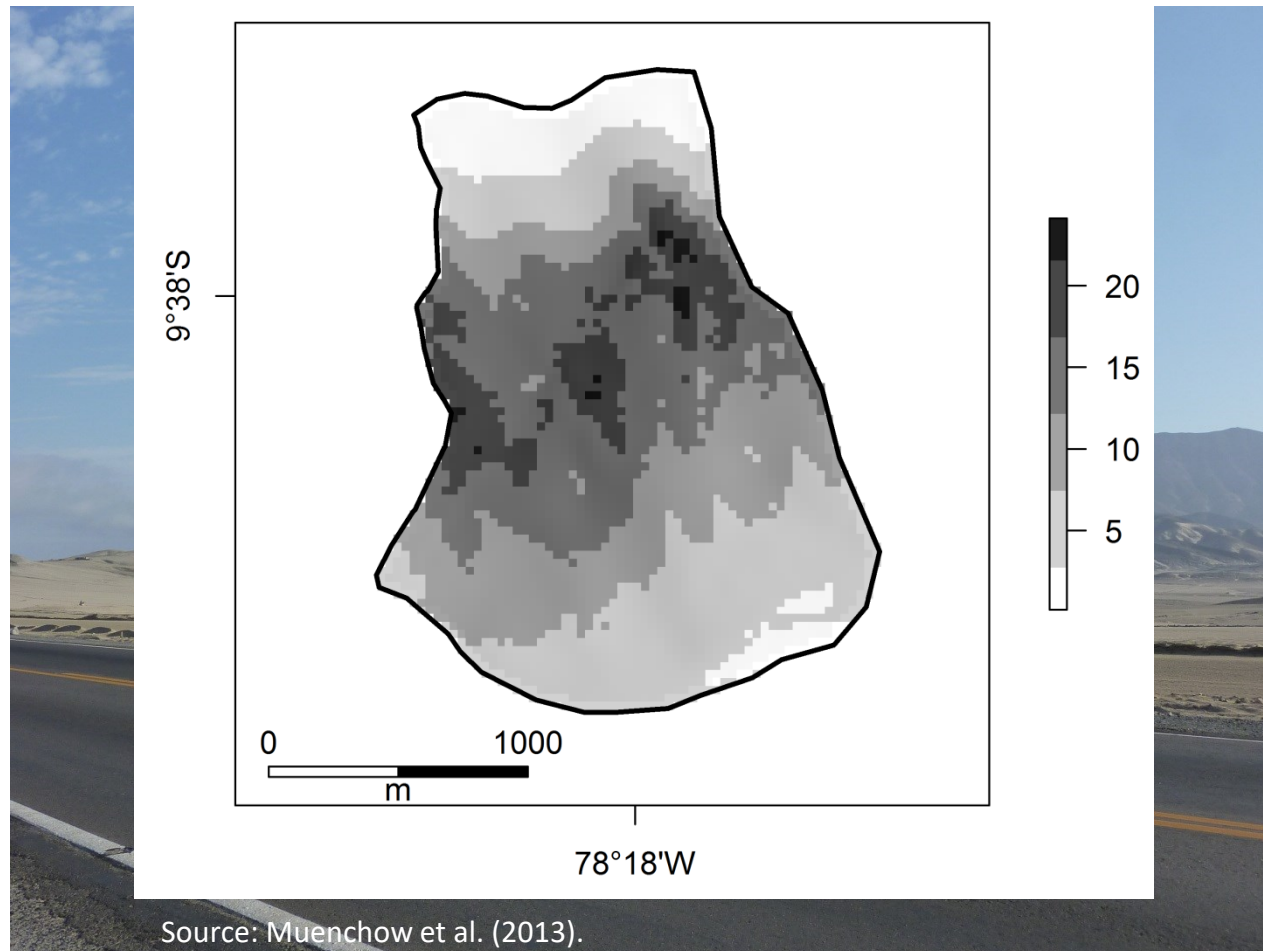
$$Y_i \sim P(\mu_i) \text{ and } E[Y_i] = \mu_i = e^{\alpha + \beta_1 X_{1i} + \dots + \beta_n X_{ni}}$$

$$\log(E[Y_i]) = \alpha + \beta_1 X_{1i} + \dots + \beta_n X_{ni}$$



log-link

# Modeling species richness



# Binomial GLM

**Absence (= 0)**

1. Express 0 and 1 as probability  $P$
2. Apply a series of transformations on  $P$
3. back-transform to 0-1 intervall



**I am not here, because  
the habitat is not good!**



**Here we are!**

**Presence (= 1)**

modified after Zuur et al. (2009).



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# Concept of Odds

$$O_i = \frac{\pi_i}{1 - \pi_i}$$

with  $O_i$  = Odds for the  $i$ th observation

$\pi_i$  = Probability of the  $i$ th observation

-> Value not any longer restricted to 0 and 1!!!

# Concept of Odds

$$O_i = \frac{0.9}{(1 - 0.9)} = 9$$

Odds of 9 -> it is **9 times more likely** to record a hippo than not to record one.

Or: In **9 from 10** plots you will find a hippo.

**Absence (= 0)**



I am not here, because the habitat is not good!



Here we are!

**Presence (= 1)**

modified after Zuur et al. (2009).



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# log-Odds as a function of predictor values

log-link  $\leftarrow \log\left(\frac{\pi_i}{1 - \pi_i}\right) = \eta$

with  $\eta$  = predictor function

-> Negative values are possible



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## Solving for $\pi_i$

$$\pi_i = \frac{e^\eta}{1 + e^\eta}$$

-> term lies always between 0 and 1 (back-transformation)!!!



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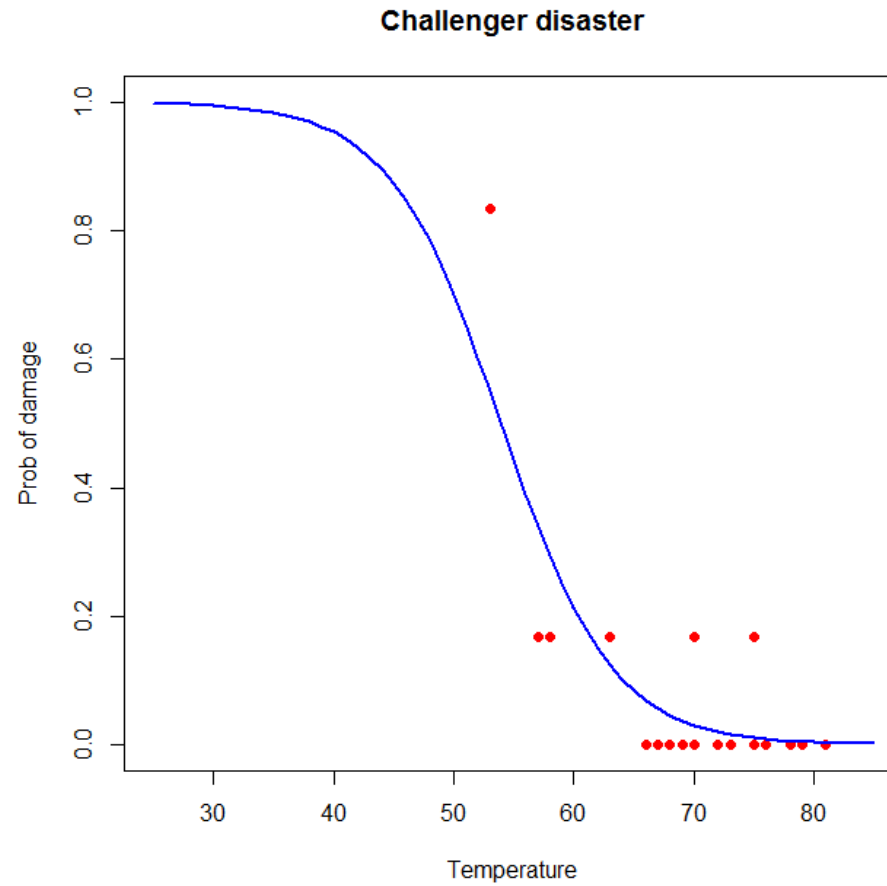
# Logistic regression prediction formula

$$Y_i \sim B(1; P_i) \text{ and } E[Y_i] = P_i = \pi_i = \frac{e^{\alpha + \beta_1 X_{1i} + \dots + \beta_n X_{ni}}}{1 + e^{\alpha + \beta_1 X_{1i} + \dots + \beta_n X_{ni}}}$$

- appropriate distribution (Bernoulli)
- Maximum likelihood algorithm (see Zuur et al., 2007: 93)



# Example: Challenger disaster



Source: Faraway (2006).

# Modeling landslide susceptibility

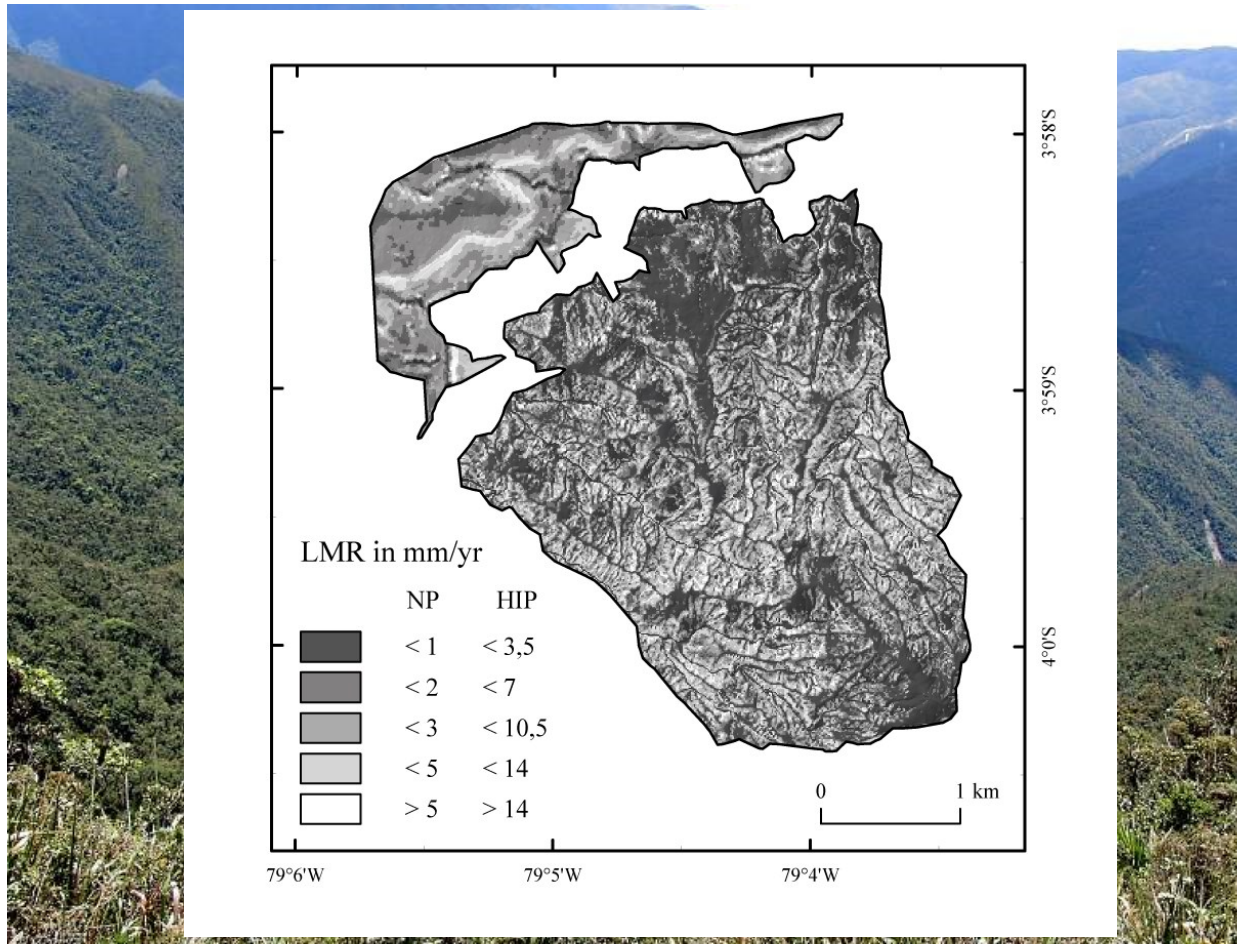


Foto: Michael Richter.

Source: Muenchow et al. (2011).



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