Hidden variable approach
how to deal with lo

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Objectives:

* understand spatio-temporal properties of precipitation
* unify "mean" calculations and probability calculations for quantities that frequently equal 0

Idea:

Gauge precipitation R is related to a *hidden* variable W so that [1]:

$$\begin{cases} W = R^{1/\beta}, & R > 0 \\ W < 0, & R = 0 \end{cases}$$

Thus, W is power-transformed and assumed to be *negative* when the observed precipitation is 0.
Practically, $W < 0$ is treated as *missing* and is imputed in our model fit.

The transformation and imputation of W are done to insure W has *normal* distribution (we have used $\beta = 2$). Normality enables us to use traditional techniques like kriging.

W will be called *precipitation potential*.

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* The model distinguishes between "season normal" μ_d mean potential, and year-specific potential θ_t.

Estimation: Bayesian approach

Computation using *Gibbs sampler* requires finding *full conditional posteriors* (FCP)
Let $(X_1, X_2, ..., X_n)$ be the vector of all unknown quantities and parameters.

Markov Chain Monte-Carlo algorithm through Gibbs sampling:

1. Draw a sample from FCP of one X_j given all other parameters and the data:

$$p(X_j \mid X_1, ..., X_{j-1}, X_{j+1}, ..., X_n, \texttt{data})$$

2. Cycle repeatedly for $j = 1, ..., n$

The algorithm obtains (correlated) samples from parameters of interest.

For example, FCP for W_{it} is just $R_{it}^{1/\beta}$ when $R_{it} > 0$, and is truncated Normal(mean = Z_{it}, st.dev.= τ) when $R_{it} = 0$.

Use for prediction: to predict probability of precipitation at site i, time t, generate samples of W_{it} and count the