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Supplement of

GPRChinaTemp1km: a high-resolution monthly air temperature data set for China (1951–2020) based on machine learning

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