Approach	Core idea (mapping)	Typical use cases	Advantages	Disadvantages	Can incorporate static predictors?
PP (Perfect Prognosis)	Train an algorithm on coarse-scale prognostic variables from reanalysis (thermodynamic + dynamic fields at multiple levels) to predict local surface climate variables (e.g., station or high-res local variable from reanalysis). After training, apply the learned relationships to GCM predictors (domain adaptation).	• Downscaling of historical and future GCM data to local/regional scales. • Use of large-scale circulation/thermodynamic fields (Z, T, winds, humidity, SLP, etc.) to obtain local temperature/precipitation/extremes. • Situations where you want a GCM-independent, transferable statistical model.	• Uses physically meaningful large-scale predictors; often more interpretable. • Trained in obs/reanalysis space, then applicable to multiple GCMs (not model-specific). • More flexible and generalizable; conceptually close to the role of an RCM.	• Assumes that reanalysis-derived relationships remain valid under GCM biases and future climates (stationarity issue). • Performance sensitive to predictor choice and quality of reanalysis/observations. • Does not directly correct model-specific biases in the target variable; residual systematic errors may remain when applied to biased GCM output.	Yes**.** Statics are commonly included as covariates to represent local site effects (e.g., station/grid elevation, orography, distance to coast). They complement large-scale dynamic predictors.

Approach	Core idea (mapping)	Typical use cases	Advantages	Disadvantages	Can incorporate static predictors?
MOS (Model Output Statistics)	Directly bias-correct GCM/forecast output fields by learning a statistical linking function between coarse-scale model fields and local observed data, when day-to-day correspondence (between large and local scale variables) is weak. Adjustments are per-model (non-transferable).	• Bias correction and calibration of a specific forecast system (ensemble mean/quantiles, lead-time dependent). • Operational post-processing for temperature, wind, precipitation probabilities.	• Directly targets model-specific systematic errors (mean, variance, distribution tails). • Can work even without strong day-to-day correspondence (distribution-based methods). • Simple to implement operationally and widely used in climate services.	• Typically not transferable between GCMs or model versions; needs retraining per model/system. • Focus on statistical adjustment can break multivariate or spatial consistency if not carefully designed. • Often corrects distributions but does not change underlying model dynamics; may still misrepresent processes.	Yes, in principle. Static covariates (elevation, exposure, land cover, etc.) can be included in regression-type MOS schemes, though many classical distribution-based MOS implementations use only the model variable(s) and time/season information.

Approach	Core idea (mapping)	Typical use cases	Advantages	Disadvantages	Can incorporate static predictors?
SR (Super Resolution)	A combination of PP & MOS in which a coarse-resolution version of the same surface field (e.g., coarse precipitation or temperature) is used to predict its high-resolution gridded counterpart → fine between two observational/reanalysis products, with the predictand being a spatial field rather than a station time series.	• SR is mainly for coarse res -to-high res reconstruction of the same target variable, to recover fine-scale spatial structure (orography, coastlines, local gradients). • SR is not MOS-style calibration by default, because it is typically not trained on a specific forecast system's outputs. • SR is not PP-style physical downscaling, since it usually does not use circulation or thermodynamic predictors.	• Conceptually simple predictor–predictand pairing (same variable, different resolution). • Naturally tailored to spatial refinement; can make use of fine-scale patterns present in the high-resolution reference. • Fits well with ML/SR architectures (CNNs, U-Nets, transformers), since it is formulated as an image-to-image problem.	• Since only the coarse target variable is used, lacks explicit large-scale dynamical context (no winds/SLP etc.). • Strongly tied to the training reference dataset; domain adaptation to GCM fields is non-trivial. • Risk of adding fine-scale detail that is visually plausible but not physically accurate, especially for precipitation/extremes.	Yes. Static fields (e.g., orography, land–sea mask, land cover, slope/aspect) are often crucial auxiliary inputs to guide the coarse → fine mapping spatial patterns.