template in Table 4.2. If you also wish to include covariate and supplementary variables in the analysis, you must open the Advanced Constrained Analyses folder.

A fast way to obtain both a constrained and an unconstrained ordination of the same response data is to use the *Compare-constrained-unconstrained* template. In addition to the defined ordinations, the template results in a specialized page in the Analysis Notebook with cross-correlations of constrained and unconstrained axes and an efficiency measure of the constrained axes (see section 5.3.10 and section 6.2.2.1 for an example). An alternative way of comparing ordination is via the *Analysis | Add new analysis | Compare ordinations* command (see example Spider1 in section 6.2.1).

The axes of a constrained ordination can be tested for their statistical significance by using the *Test-constr-axes* template (see section 2.5 and the Spider2 project in section 6.2.2 for examples). The method is described in Legendre et al. (2011). The last template in Table 4.2 is *Interactive-forward-selection* template which is also illustrated in section 2.5.

Table 4.2 Standard analysis templates[1] for unconstrained and constrained ordination methods. RV = Response variables. The unconstrained methods allow covariates (partial ordination) to be included.

Standard analyses	Model & Methods	Brief summary
Unconstrained	*RV* ~ |* PCA, CA, DCA	Unconstrained ordination of response data-table, with optionally specified covariates
Unconstrained-covariates	*RV*~ | *Covars* Partial PCA, CA, DCA	Unconstrained partial ordination of response data
Unconstrained-suppl-vars	*RV* ~[*SupplVars*] | * PCA, CA, DCA with supplementary variables	Unconstrained ordination with supplementary data projected and covariates optionally set in Analysis Setup Wizard
Constrained & Constrained-P	*RV* ~ *ExplVars* RDA, CCA	Constrained ordination
Compare-constrained-unconstrained	*RV* ~ *ExplVars* (step 1) *RV*~ [*ExplVars*] (step 2)	Compare constrained and unconstrained ordination for the same response data
Test-constr-axes	*RV* ~ *ExplVars*	Test of significance for individual constrained (canonical) ordination axes
Interactive-forward-selection	*RV* ~ *ExplVars*	Constrained ordination with explanatory variables interactively chosen

[1]PCA = principal components analysis, CA = correspondence analysis, DCA = detrended correspondence analysis, RDA = redundancy analysis, CCA = canonical correspondence analysis.

4.3.4.2 Variation Partitioning Analyses

The Variation Partitioning Analyses (Table 4.3) partition the variation (variance or inertia) in the response data into parts attributed to sets of explanatory variables (Borcard et al. 1992, Økland & Eilertsen 1994, Peres Neto et al. 2006, Legendre & Legendre 2012, pp. 570-581). There are separate templates for two and for three sets of explanatory variables.

Table 4.3 Variation Partitioning Analyses. RV = Response variables, EV* = set of explanatory variables. Example projects are DuneVarPart and Oribatids described in sections 6.3.1 and 6.3.2, respectively.

Variation Partitioning	**Model**	**Brief summary**
Var-part-2groups-Conditional-effects-tested	*RV ~ EV1+EV2*, *RV ~ EV1 | EV2*, *RV ~ EV2 | EV1*	Variation partitioning between two groups of predictors, testing the unique effects
Var-part-2groups-Simple-effects-tested	*RV ~ EV1+EV2*, *RV ~ EV1*, *RV ~ EV2*	Variation partitioning between two groups of predictors, testing the simple effects
Var-part-2groups-Simple-effects-tested-FS	*id.*	Variation partitioning between two groups of predictors with forward selection of the members of each group
Var-part-3groups-Conditional-effects-tested	*RV ~ EV1+EV2+EV3*, *~ EV1 | EV2+EV3*, *~ EV2 | EV1+EV3*, *~ EV3 | EV1+EV2*, *~ EV1 | EV3*, *~ EV2 | EV1*, *~ EV3 | EV2*	Variation partitioning between three groups of predictors, testing the unique effects
Var-part-3groups-Simple-effects-tested	*RV ~ EV1+EV2+EV3, ~ EV1+EV2, ~ EV1+EV3, ~ EV2+EV3, ~ EV1*, *~ EV2*, *~ EV3*	Variation partitioning between three groups of predictors, testing the simple effects
Var-part-3groups-Simple-effects-tested-FS	*RV ~ EV1+EV2+EV3, ~ EV1+EV2, ~ EV1+EV3, ~ EV2+EV3, ~ EV1*, *~ EV2*, *~ EV3*	Variation partitioning between three groups of predictors with forward selection of the members of each group
Var-part-PCNM	*RV ~ ExplVars* + [*], *Spatial*~{PCNM}, *~PCNM* + [*], *~ ExplVars + PCNM* + [*], *~ ExplVars* + [*] | *PCNM*	Variation partitioning separating the effects of spatial variation (and autocorrelation) from the effect of other predictors
Var-part-PCNM-FS	*id.*	Variation partitioning separating the effects of spatial variation from the effect of other predictors chosen by a forward selection
Var-part-PCNM-FS-covariates	*id.*	Same as *Var-part-PCNM-FS* except the presence of *a priori* covariates e.g. for trend removal

The variation parts can be calculated in two different ways. Templates with *Conditional effects* in the name perform statistical tests on the unique effects of each set (its conditional effect) and assign each set in turn to the covariate role. The templates with *Simple effects* in the name perform statistical tests on the simple effects of each set (its marginal effects) and do not assign any set to the covariate role. The distinction between these templates is well reflected in their formulae. For example, "*EV1|EV2*" in the formulae for the first template indicates that the first and second set of explanatory variables take the explanatory and covariate role, respectively. The step of the analysis based on this formula yields the test of conditional effects of the first set given the second set. By contrast, no conditional sign (..|..) is used in the second template. Therefore, the effects tested are simple effects (ignoring the other set of variables).

With many variables in one or more sets, forward selection can also be useful to select a parsimonious set to explain the response data. This can be achieved with the templates with *FS* in the name. The abbreviation PCNM stands for principal coordinates of neighbour matrices and its template is useful when one set of explanatory data is best represented by a distance matrix (either pre-computed or computed from existing variables). The method was proposed by Borcard et Legendre (2002) for separating the variation due to space from that due to other explanatory variables. In their approach, space is represented by (geographic) distances among cases. These templates also perform a permutation test of the joint effect of all the candidate members of each group, as recommended by Blanchet et al. (2008). Examples and further references are provided in the Oribatids project (section 6.3.2). Legendre & Legendre (2012, p. 861) refer to PCNM scores as dbMEM (distance-based Moran' eigenvector maps). PCNM implementation in Canoco 5 follows their recommendations, which were originally suggested by Dray et al. (2006).

The analysis templates for variation partitioning that use the forward selection of group members (this is always done for the group representing spatial variation, in the two PCNM templates) also perform a permutation test of the joint effect of all the candidate members of each group, as recommended by Blanchet et al. (2008).

4.3.4.3 Advanced Constrained Analyses

Table 4.4 summarizes the ten templates in the Advanced Constrained Analyses folder. The first four templates in Table 4.4 do calibration (for inputing missing explanatory data values, section 3.2), principal response curves (van den Brink & ter Braak 1998, 1999) or are handy for spotting outliers in the explanatory data. See the indicated example projects of Chapter 6 for details. The last six templates extend those of the Standard Analyses folder by allowing covariates or supplementary variables in the analysis. Templates with covariates are indicated with the term "partial" in their name.