35 Sea level change and salt marshes in the Wadden Sea: A time series analysis

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35.1 Interaction between hydrodynamical and biological factors

Salt marshes are a transitional zone between the sea and land formed by flooding, sedimentation and erosion. This highly specialized zone is characterised by a close interaction of physical and biological processes. The saline plant and animal communities play an important role in the geomorphological development. Because the salt marshes are a sedimentary belt, their potential for recovery is essential to coastal protection (Erchinger 1995).

The Danish-German-Netherlands Wadden Sea harbours substantial areas of salt marshes. With 400 km^2, first place in Europe is shared with the United Kingdom (Dijkema 1990; Bakker et al. 2005). In the Netherlands part of the Wadden Sea, 3.6% of the total tidal area is salt marsh, divided into a barrier island-type and a mainland-type of salt marsh. In the past, embankments have far exceeded the natural accretion rate of the mainland-type of salt marsh. Therefore, the total salt marsh area decreased. By stimulating the sedimentation process through the creation of sedimentation fields sheltered by brushwood groynes and improving vegetation development through artificial drainage (digging creeks) the man-made mainland salt marshes in the provinces of Friesland and Groningen (Figure 35.1) helped to catch up on this backlog over the past decades.

Salt marsh plants play an essential role in the interaction between hydrodynamical and biological factors. In general, salt marsh development is possible on locations with a gently sloping coastline, low wave energy and low water velocity. Therefore, salt marshes are absent on exposed rocky coastlines, but they are usually present along flat coasts and in sheltered bays. If there is sufficient sediment in the water, the tidal flat increases in surface level and the pioneer plants *Spartina anglica* and *Salicornia dolichostachya* appear (Figure 35.2). At around mean high tide (MHT) level, the grass *Puccinellia maritima* is the next step in the marsh building process. This perennial grass provides sufficient cover (i) to produce the highest accretion rate in the entire development of the salt marsh, (ii) to prompt the development of a natural creek system, and (iii) to fix the newly deposited sediments. The development of a creek system (or the digging of ditches in man-made salt marshes) provides a major stimulus for the growth of most salt marsh plants by improving drainage. Several studies have shown that the mud supply in the Wadden Sea is more than sufficient and therefore in no way restricts the rate of accretion of the mainland salt marshes. Due to artificial draining in mainland salt marshes, no major spatial patterns in sedimentation can be found. This contrasts with the barrier island-type of salt marshes where creeks, levees and basins are natural phenomena.

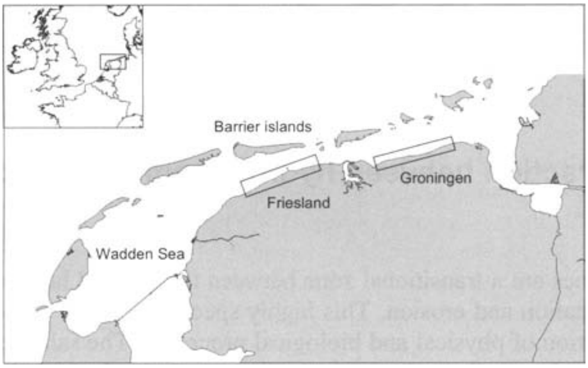

Figure 35.1. Location of mainland salt marsh areas (in rectangles) in Friesland and Groningen.

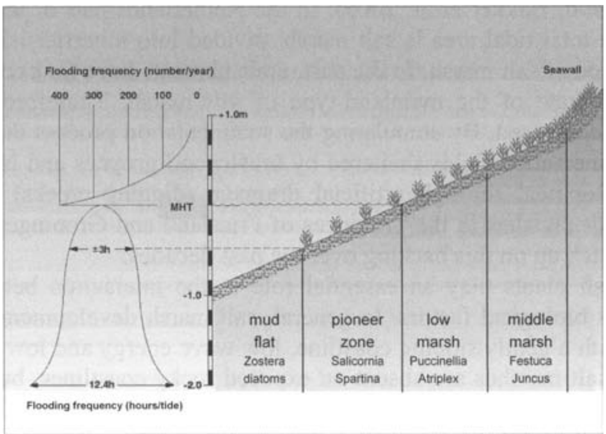

Figure 35.2. Schematic overview of the zonation of the vegetation in a typical salt marsh as a consequence of flooding frequency and MHT. The pre-pioneer zone is the transition between pioneer zone and mudflat and has a scarce vegetation cover (Erchinger 1985).

Salt marsh plants have a characteristic vertical range in relation to sea level. For long-term vegetation development, the accretional balance of sedimentation, erosion, sea level rise and soil subsidence is thought to be the determining factor (Dijkema 1997). Salt marsh plants have a characteristic vertical range in relation to sea level. Year-to-year changes in MHT (Figure 35.3), however, have an impact on the distribution of plants and on the vegetated area of the different salt marsh zones, under the precondition that the drainage pattern does not change (Olff et al. 1988; Dijkema et al. 1990; De Jong and Van der Pluijm 1994). The number of yearly floodings changes with MHT. The lower limits of the vegetation zones may follow trends of changing water level. An increase in flooding frequency may worsen growing conditions and shift the lower limits of vegetation zones to higher grounds that are less frequently inundated. A decrease in flooding frequency may improve growing conditions at lower levels and will stimulate the plants to move to lower levels (= towards the mudflat). An increase in MHT of just 5 to 10 cm in a single year may already result in a shift of some plant species (Beeftink 1987).

The main questions in this case study chapter are (i) do the year-to-year changes in MHT levels affect the development of salt marsh vegetation, (ii) are MHT levels responsible for major shifts in the lower limits of the vegetation zones, and (iii) are the impacts on pioneer zone and salt marsh zone different?

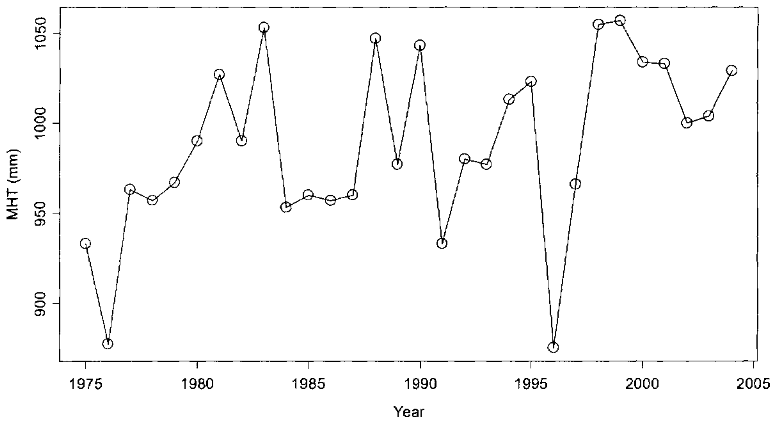

Figure 35.3. Yearly MHT in the Netherlands Wadden Sea 1975–2004.

35.2 The data

The time series used in this chapter are taken from a large dataset on man-made salt marshes along 50 km of the Dutch mainland coast collected by the Department of Public Works (Wadden Sea Unit) between 1937 and 2004. The database includes records on elevation, accretion, soil composition, vegetation composition, vegetation coverage, vegetation type, yearly average MHT, management, etc.

(Dijkema 1997). It is probably the oldest and largest monitoring dataset for a salt marsh site in Europe. We selected 18 stations (Table 35.1) located in the provinces of Groningen and Friesland. For each station, information of plant community relevees were used to calculate the yearly lateral seaward shifts of the lower limits of the pioneer and marsh zones in metres. Hence, PP_GR_East is an annual time series that consists of the distance from the seawall the boundary of the pre-pioneer species at location east in Groningen, relative to 1980. The same holds for PP_GR_Mid, but now for a different location. We use the yearly MHT for all zones (Figure 35.3). Figure 35.4 shows the man-made salt marshes along the mainland coast of Groningen.

Table 35.1. Names of the 18 time series used in this case study chapter. There are three vegetation zones, namely pre-pioneer zone (0–5 % coverage), pioneer zone (> 5 % coverage) and salt marsh. For each vegetation zone, there is an east, mid and west time series referring to the position of the stations.

	Area	
Type	**Groningen**	**Friesland**
Pre-pioneer	PP_GR_East	PP_FR_East
Pre-pioneer	PP_GR_Mid	PP_FR_Mid
Pre-pioneer	PP_GR_West	PP_FR_West
Pioneer	P_GR_East	P_FR_East
Pioneer	P_GR_Mid	P_FR_Mid
Pioneer	P_GR_West	P_FR_West
Salt marsh	K_GR_East	K_FR_East
Salt marsh	K_GR_Mid	K_FR_Mid
Salt marsh	K_GR_West	K_FR_West

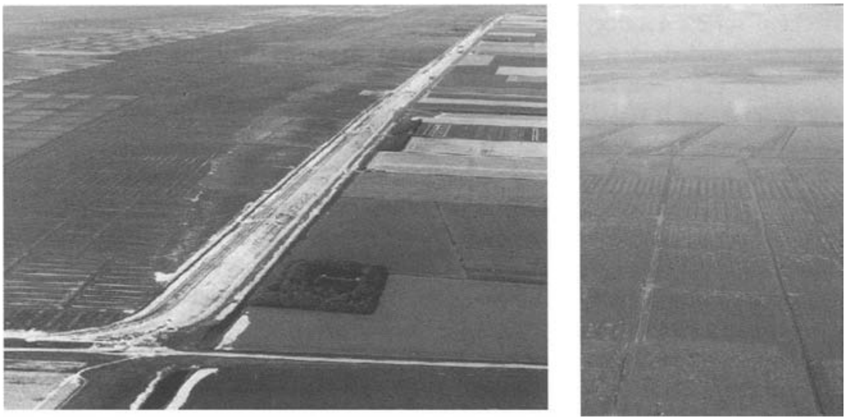

Figure 35.4. Left: Salt marsh works in Groningen. The sea wall is the white wall in the middle of the photo. The different vegetation zones (salt marsh, pioneer and pre-pioneer) can be seen by moving from the sea wall towards the left. The land on the right side of the seawall is never flooded and is used for agriculture. Right: Salt marsh works viewed from the sea wall to the mudflat.

35.3 Data exploration

Figure 35.5 shows a principal component analysis (PCA) correlation biplot for the nine time series from Groningen and the nine series from Friesland. Most of the Groningen time series point in the upper right direction, whereas the majority of the Friesland series point towards the lower right. Recall from Chapter 12 that lines pointing in the same direction implies that the corresponding variables are correlated, whereas if the angle is 90 degrees, they are uncorrelated (although keep in mind that the biplot is a two-dimensional approximation of a high-dimensional space). Hence, the biplot indicates that the nine time series of Groningen behaved differently from those in Friesland, and therefore, we will analyse the data in two steps, first for the Groningen series and then for the Friesland series.

We have nine time series for Groningen; three pre-pioneer, three pioneer and three salt marsh time series and a lattice plot are presented in Figure 35.6 (left). Data from 1975 onwards were used as this provides a regular-spaced dataset without missing values. Most of the series exhibit a general decline over time. This means that the lower limits of the three vegetation zones are moving towards the sea wall. Two time series (PP_GR_East and PP_GR_Mid) have a large peak in the mid-1990s but as it is present in more than one time series is unlikely to be a typo. Note that this peak also coincides with the low MHT value in 1996. There is no immediate reason to apply a data transformation. The lattice graph for the Friesland series is presented in Figure 35.6 (right). Again, there is no need for a data transformation. Both lattice graphs of the time series versus Year indicate that there are indeed differences in the temporal patterns in the Groningen and

Friesland series. Lattice graphs of the time series versus MHT are presented in Figure 35.7 and show a weak linear relationship at most stations.

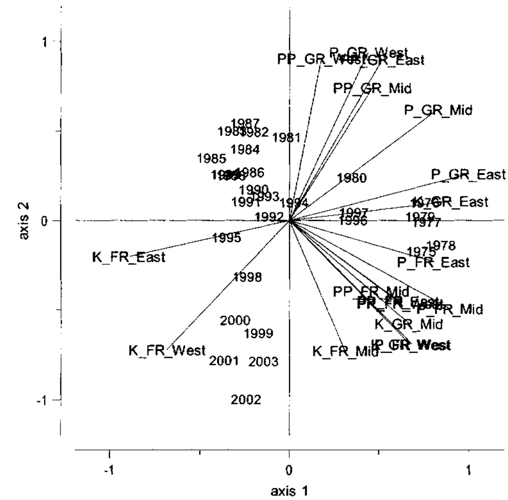

Figure 35.5. PCA correlation biplot of all 18 time series from Groningen and Friesland. Lines pointing in the same direction indicate high correlation. The first two eigenvalues are 0.36 and 0.30, respectively, corresponding to 66% of the variation in the data. The software used scales the eigenvalues such that the sum of all eigenvalues is equal to 1.

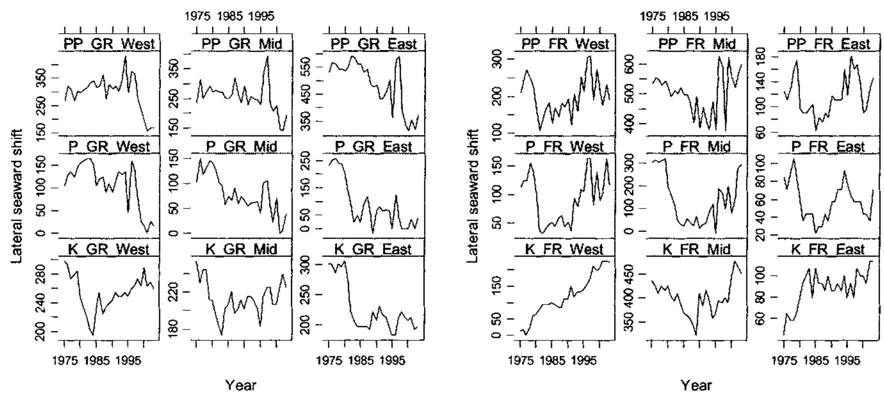

Figure 35.6. Left: Time series for Groningen (GR) based on yearly lateral seaward shifts of pre-pioneer (PP), pioneer (P) and salt marsh zone (K) plotted versus Year. Right: Time series for Friesland (FR) based on yearly lateral seaward shifts of pre-pioneer (PP), pioneer (P) and salt marsh zones (K) plotted versus Year.

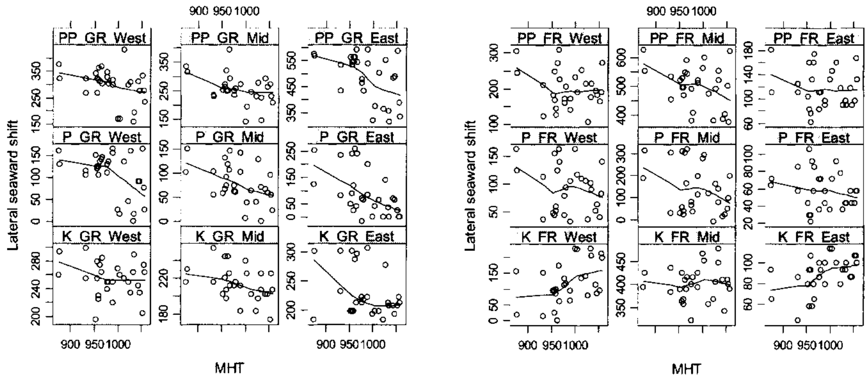

Figure 35.7. Left: Time series for Groningen (GR) based on yearly lateral seaward shifts of pre-pioneer (PP), pioneer (P) and salt marsh zones (K) plotted versus MHT (mean high tide). A smoothing LOESS curve was added. Right: Time series for Friesland (FR) based on yearly lateral seaward shifts of pre-pioneer (PP), pioneer (P) and salt marsh zones (K) plotted versus MHT (mean high tide). A smoothing LOESS curve was added.

35.4 Additive mixed modelling

Based on prior knowledge, we expect to find a linear relationship between MHT and any of the time series. The question is whether this relationship is *indeed* linear for these data, and whether there is also a temporal trend in the time series. A possible modelling approach is a linear regression model of the form:

$$Y_t = \alpha + \beta_1 \mathrm{MHT}_t + \beta_2 t + N_t \qquad (35.1)$$

In equation (35.1), Y_t is the value of the lateral shift of the lower limit of the vegetation zone at a particular station in year t, α is the intercept, MHT_t is the mean high tide in year t, the component $\beta_2 t$ is a trend over time and N_t is independently normally distributed noise. The parameter β_1 tells us whether there is a linear effect of MHT on the time series and the slope β_2 represents the effect of the remaining trend. There are three potential problems with this model: (i) the effect of MHT might not be linear (and the shape of the LOES smoothers in the lattice plots gave some indication that this indeed may not be the case), (ii) the trend might not be linear, and (iii) the noise component might not be independent. The first two issues can be dealt within the additive modelling framework:

$$Y_t = \alpha + f_1(\mathrm{MHT}_t, \lambda_1) + f_2(\mathrm{Year}, \lambda_2) + N_t \qquad (35.2)$$

The function $f_1(\mathrm{MHT}_t, \lambda_1)$ is a smoothing curve for MHT and can have any shape. The amount of smoothing is determined by λ_1. If $\lambda_1 = 1$, then the smoothing curve is a straight line making it identical to the β_1MHT$_t$ component in the linear regression model. The function $f_2(\text{Year}_t,\lambda_2)$ is the trend over time, and again, it can have any shape depending on the amount of smoothing λ_2 (the degrees of freedom of the smoother). So, using smoothing curves in equation (35.2) instead of parametric components in equation (35.1) allows for non-linear relationships. The amount of smoothing for each smoother can be determined with the AIC or with an automatic selection tool like the cross-validation; see Chapter 7 for further details.

So, what do we do with the noise component? As in this study the positions of the lower limits of the various vegetation zones were measured repeatedly at the same locations over a long period, the errors will not be independent. In various chapters (8, 16, 22, 26), we discussed how linear regression can be extended to generalised least squares by imposing for example an ARMA(p,q) structure on the noise component N_t in equations (35.1) or (35.2). Recall that such an error structure is of the form:

$$N_t = \gamma_1 N_t + \ldots + \gamma_p N_p + \varepsilon_t + \phi_1 \varepsilon_{t-1} + \ldots + \phi_{t-q} \varepsilon_{t-q} \tag{35.3}$$

The same can be done in the additive model in equation (35.2), which is then confusingly called additive mixed modelling (Wood 2006). The parameter p in equation (35.3) defines the number of auto-regressive error terms N_t and q the number of moving average terms. The noise component ε_t is independently normally distributed. The only purpose of equation (35.3) is to break down the *dependently* distributed noise term N_t into smaller building blocks that consist of past noise terms of N_t and something that is indeed independently and normally distributed. The question is then how many of these building blocks we need. The strategy we adopt here is to try different values of p and q and use the one with the lowest AIC. If it turns out that $p = q = 0$ is the most optimal combination, then we are close to assuming that the original error term N_t is independent. We deliberately used the phrase 'close to' as we could also try other types of error structures (Pinheiro and Bates 2000).

More problems

There is an extra problem. We have one smoothing model for each of the 18 time series. Even if we analyse the data from the two provinces separately, we still have nine models per province. To reduce this number, one model with interaction terms can be applied:

$$Y_{ti} = \alpha_i + f_{1i}(\text{MHT}_t, \lambda_{1i}) + f_{2i}(\text{Year}, \lambda_{2i}) + N_{ti} \tag{35.4}$$

Y_{ti} is the value of the lateral shift of the lower limit of the vegetation zone in year t at station i, where i = 1,..,9. Each station can have its own smoother for MHT and Year. It is also possible to use one MHT smoother or one Year smoother for a couple of stations, e.g., for those close to each other (and showing the same pattern). Technically, the interaction is modelled using the 'by' command in the gamm function in the R library mgcv (Wood 2006). The alternative (although not applied here) is to use one overall smoother for MHT and one for Year, and include a smoother for each station representing the deviation from the overall pattern. Significance levels of the smoothers indicate which stations deviate form the general pattern.

So what about the noise term N_{ti}? The lattice graphs in the data exploration show that the variation between the stations differ considerably. Hence, assuming that N_{ti} is normally distributed with the same variance for each station is likely to be wrong; the model validation would show heterogeneity of residuals. Therefore, we will allow for different variances per station:

$$N_{ti} \sim N(0, \sigma_i^2) \tag{35.5}$$

Note the index i for the variance. To reduce computing time, one auto-correlation structure for all nine stations is used. As a result, the ARMA parameters do not have indices i:

$$N_{ti} = \gamma_1 N_{ti} + \ldots + \gamma_p N_{pi} + \varepsilon_{ti} + \phi_1 \varepsilon_{t-1,i} + \ldots + \phi_{t-q} \varepsilon_{t-q,i} \tag{35.6}$$

This is a practical choice driven by lack of sufficient computing power, but for smaller datasets, one can make auto-correlation graphs of the residuals for each time series and investigate whether the patterns are different.

The question is now how to find the optimal model. What is the model selection strategy? Because this is an extension of linear mixed modelling, we should also adopt the same selection strategy as in Chapter 8:

1. Start with a model that is reasonable optimal in terms of fixed components. This refers to the intercepts and smoothers in equation (35.4). Based on initial model runs with independently normally homogeneously noise, we expect that the final model is not more complex. In fact, most smoothers for MHT were linear lines, so some simplification (in later steps of this strategy protocol) may be needed.
2. Find the optimal model in terms of random components. This refers to equations (35.5) and (35.6). Do we really need the nine variances, and what is the optimal ARMA structure? We can use the AIC and likelihood ratio tests (using REML) to answer both questions
3. For the optimal random structure obtained in the previous step, find the optimal model in terms of fixed terms, i.e., drop non-significant smoothers. Just as in mixed modelling, maximum likelihood estimation instead of REML is needed.

35.5 Additive mixed modelling results

Groningen

We will apply the additive mixed model in equations (35.4)–(35.6) on the nine time series from Groningen. The three-step protocol was followed.

Step 1

Using a normally independently homogeneously distributed error term, the model in equation (35.4) was fitted. It gave a Year and MHT smoother for each station. For some stations, the smoothers were non-linear, but for the majority of stations, they were straight lines.

Step 2

Two questions are of prime interest here: (i) Do we need the nine variances or is one sufficient and (ii) which ARMA structure do we need for the auto-correlation? The first question is quite simple; fit the model in equations (35.4)–(35.6) containing nine variances, and fit a model with only one variance and apply a likelihood ratio test.

Model	df	AIC	BIC	logLik	L-Ratio	p-value
1	55	2393.12	2583.16	−1141.56		
2	47	2469.36	2631.76	−1187.68	92.2379	<0.001

Model 1 contains the nine variances and model 2 only one; hence, the differences in number of parameters is eight. Both the AIC and the likelihood ratio test indicate that the model with nine variances is preferred. A p-value smaller than 0.001 can be seen as an indication that adding nine variances does improve the model. Now the more difficult question, what values of p and q should we choose for the ARMA(p,q) structure? This is a matter of trying a series of combinations and selecting the combination with the lowest AIC. The reader is warned that this is a time-consuming exercise with about half an hour computing time per p-q combination. And if the number of parameters is increasing, choosing 'good' starting values to avoid non-convergence becomes some sort of art as well. The model with no auto-correlation structure ($p = q = 0$) had AIC = 2413. For $p = 1$ and $q = 0$ we had AIC = 2393, $p = 1$ and $q = 1$ gave AIC = 2395, $p = 2$ and $q = 2$ gave AIC = 2398, $p = 3$ and $q = 0$ gave AIC = 2397, $p = 3$ and $q = 1$ gave AIC = 2399. This clearly shows that an auto-regressive error structure of order 1 ($p = 1$, $q = 0$) should be used. A model with no auto-correlation ($p = q = 0$) is nested within a model with ARMA(1,0), also called AR(1). Hence, we can also apply a likelihood ratio test giving a p-value smaller than 0.001.

Step 3

Using nine different variances and an ARMA(1,0) error structure, we now investigate the optimal model in terms of fixed components. Cross-validation (Chapter 7) was applied to estimate the amount of smoothing for each smoother. We dropped (one by one) the smoothers that were not significant at the 5% level.

Results for the Year smoothers showed that seven of them were significant at the 5% level (with p-values all smaller than 0.004), and these are presented in Figure 35.8. Four stations show a linear decline over time (getting closer to the seawall), whereas three stations show a non-linear pattern. As to the MHT smoothers, they all had 1 degree of freedom, indicating a linear relationship between MHT and the lateral shift of the lower limit of the vegetation zone (Figure 35.8). The MHT smoother was significant for five of the nine time series in Groningen: one salt marsh series (mid), two pioneer series (west and east) and two pre-pioneer series (west and east). The relationship was negative; higher MHT corresponds to lower lateral shift values, as was expected; the lower limit of the vegetation zones moves more towards the sea wall. However, it should be noted that p-values for the significant MHT smoothers were all between 0.01 and 0.05 indicating only a weak relationship. It should be noted that the smoothing curves in Figure 35.8 are partial fits. Each smoother shows the effect, while taking into account the effect of the other smoothers. So, they are not directly comparable with the smoothers in Figure 35.7.

The numerical output for the random components shows that the autocorrêlation coefficient is equal to γ_l = 0.5, and the nine variances for the salt marsh, pioneer and pre-pioneer series are, respectively, for west, middle and east for each zone 1.00, 1.09, 1.22, 2.19, 1.92, 3.14, 2.75, 3.54 and 4.06. Note that the salt marsh series (the first three) have the lowest variances and the pre-pioneer series (the last three) the highest. Further model improvements may be obtained by using only three variances, one per vegetation type.

Because the MHT effect was linear, the following model was also applied:

$$Y_{ti} = \alpha_i + \beta_i \text{MHT}_t + f_{2i}(\text{Year}, \lambda_{2i}) + N_{ti} \tag{35.7A}$$

The MHT effect on the lateral shift of the vegetation zone is modelled as a linear term and is allowed to differ per station (this is just the interaction between station and MHT). A competing model is without the interaction:

$$Y_{ti} = \alpha_i + \beta \text{MHT}_t + f_{2i}(\text{Year}, \lambda_{2i}) + N_{ti} \tag{35.7B}$$

A likelihood ratio test gives a p-value of 0.03, indicating that the interaction term is only weakly significant. However, from model (35.7A) it is more difficult to infer for which stations MHT is important.

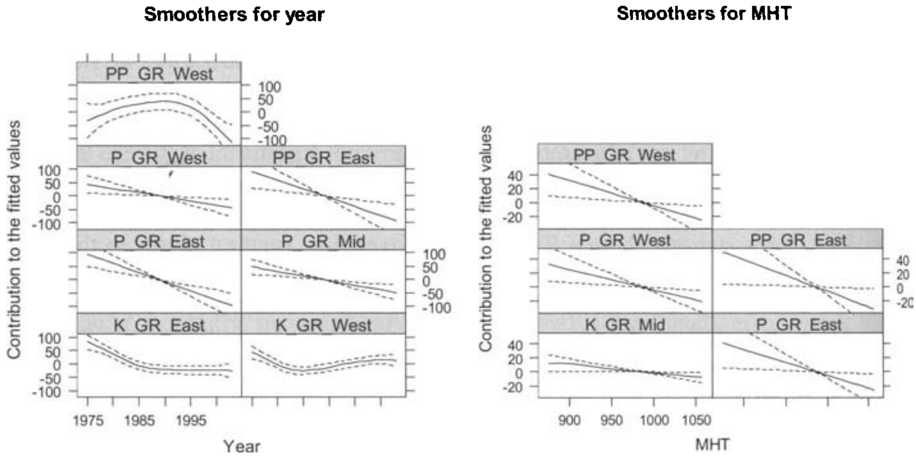

Figure 35.8. Smoothing curves for Year (left) and MHT (right) for the province Groningen. Dotted lines are 95% point-wise confidence bands.

Friesland

The same approach was applied to the nine time series from Friesland. Just as for the Groningen series, the model for the Friesland time series improved significantly by using nine variances; a likelihood ratio test (comparing models with nine and one variances) gave $p < 0.001$. The nine variances for the salt marsh, pioneer and pre-pioneer series were, respectively, for west, middle and east for each zone: 1, 1.62, 0.80, 2.08, 4.49, 1.01, 3.07, 4.10 and 1.80. As to the ARMA(p,q) autocorrelation structure, $p = q = 0$ gave AIC = 2399, $p = 1$ and $q = 0$ gave AIC = 2397, $p = q = 1$ gave AIC = 2389, $p = 2$ and $q = 1$ gave AIC = 2387, $p = 3$ and $q = 0$ gave AIC = 2388, $p = 3$ and $q = 1$ gave AIC = 2389, and $p = 3$ and $q = 2$ gave AIC = 2389. Based on these AIC values it seems that either $p = q = 1$ or $p = 2$ and $q = 1$ is the 'best' choice. We selected ARMA(1,1) as the difference between its AIC and that of the optimal ($p = 2$, $q = 1$), but a more complicated model is smaller than 2. An AIC difference of less than 2 is seen as not important enough to go for a more complicate model.

In the third step of the model selection process, we looked at the smoothers for MHT and Year. All smoothers had 1 degree of freedom, except for one station (however the smoother for this station was not significant). Only 4 from the 18 smoothers were significantly different from 0 at the 5% level, namely the MHT smoothers for stations P_FR_Mid and PP_FR_Mid (showing a linear decreasing trend over time), and the Year smoother for stations K_FR_West and K_FR_East (showing a linear increasing trend over time).

Generalised least squares

A possible criticism on the additive mixed model is that the trend at each station is modelled with a smoother, whereas parametric models are easier to present in terms of numerical and graphical output. The results of the additive mixed model suggest that MHT has a linear effect and that time is slightly non-linear for some of the time series. For those time series where time had a non-linear effect, the shape of the smoothing curve is similar to that of a second order polynomial function. So, if we want to use a parametric model that is capable of similar fitted curves, we could use a model of the form:

$$Y_{it} = \alpha_i + \beta_{1i}\mathrm{MHT}_{ti} + \beta_{2i}\mathrm{t} + \beta_{3i}\mathrm{t}^2 + N_{ti} \tag{35.7}$$

Instead of the smoother for Year, we now use a second-order polynomial function. We have added the index i that takes values from 1 to 9, and it identifies the nine stations series. The interaction allows for different relationships per station. The noise component can again be modelled using an ARMA(p,q) structure as in equation (35.3), and different variances per station can be used. It is advisable to centre the explanatory variables to reduce collinearity. The model selection process follows the same strategy as above; start with a reasonable model in terms of fixed components, find the optimal random structure, and drop all non-significant fixed terms one at a time. The parameters in the model in equation (35.7) can be estimated using generalised least squares. The problem of the model in equation (35.7) is that it results in a large number of estimated parameters for the stations and its interaction terms with time and MHT. In some situations, we might not be interested in station effects. So why should we sacrifice so many precious degrees of freedom? We can avoid this by applying linear mixed modelling and use station as a random component (Chapter 8). We can even apply such a model on all 18 time series at the same time. It would model the 18 plant zones time series as a function of an overall MHT and time effect, and at each of the 18 stations, a random variation of the intercept and slopes is allowed. Obviously, we still have to allow for an auto-correlation structure on the error components N_t, but this can be done with the ARMA(p,q) structure. If the homogeneity assumption is violated in the mixed model, then different variance components can be used. Further nominal explanatory variables identifying the two different provinces (Groningen and Friesland) could be added. We leave this as an exercise for the reader.

35.6 Discussion

Based on the results the answer to the questions (i) do the year-to-year changes in MHT levels affect the development of salt marsh vegetation, (ii) are MHT levels responsible for major shifts in the lower limits of the vegetation zones, and (iii) are the impacts on pioneer and marsh zones different is threefold yes.

On the 9 time series from Groningen, we applied a model that contained 18 smoothers: a Year smoother and an MHT smoother for each station. We then dropped the non-significant smoothers (one at a time) and ended up with a model containing seven significant Year smoothers and five significant MHT smoothers. Using cross-validation, all MHT smoothers had 1 degree of freedom indicating a linear effect. This effect was negative, which means that high MHT values are associated with a vegetation boundary close to the seawall.

The same process was applied on the nine Friesland time series, but results were less 'good' from a statistical point of view. With 'less good' we mean that we could find less significant smoothers. Only two stations had a significant (linear and negative) MHT effect and a significant Year effect.

These results indicate that MHT has a greater influence in Groningen, and this area also exhibits more significant long-term trends (the Year smoother). The terms 'greater' and 'more' are in terms of number of stations. A possible explanation for this is that in Groningen there is more sandy soil, lower sedimentation rate and maintenance problems with the groyne system. These factors offer the vegetation less protection against waves and currents allowing the physical forces to do their job.

For the Groningen series, MHT had a significant negative effect on two pre-pioneer, two pioneer and only one salt marsh series. It is tempting to conclude from this that the effect of MHT levels on the development of the salt marsh zone is minimal (at least in Groningen), due to the stronger resistance of the perennial vegetation. If this is indeed the case, then this means that we have to focus on (protection of) the pioneer zones for coastal defence. This is an important piece of information for our knowledge on the effects of enhanced sea level rise on coastal salt mashes and for coastal defence!

In the models we used a smoother for MHT and Year. The second term represents the long-term trend. A collinearity problem arises if MHT itself contains a strong long-term trend, which is not the case here as can be seen in Figure 35.3.

In this chapter, we applied additive mixed modelling. We could also have applied DFA or MAFA (Chapters 16 and 17) on these data. In fact, we did and the results were similar. We could have added another section to this chapter with the DFA and MAFA results, but then it would have been a copy of the Hawaiian bird time series case study chapter. However, it does show that if one has a multivariate time series dataset, and if the main focus is on trends and the effects of explanatory variables, then the reader of this book has now a series of useful techniques in his or her toolbox. Which tool to use (AMM, GLS, DFA or MAFA) is matter of personal preferences, size of the data and underlying questions. A few points to consider: MAFA cannot cope with missing values, DFA cannot cope well with datasets containing lots of time series (>25), AMM cannot cope well with a large number of interactions, GLS creates lots of estimated parameters, and the model selection process in mixed modelling is complicated. On the other hand, all these methods were applied in the three case study chapters and each time they did the job.