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Evaluation and design of fisheries management plans. Detecting the impact of management measures on fisheries dynamics using distance correlation

Finlay Scott, Ernesto Jardim

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1 Summary

The development and implementation of fisheries management plans can be expensive and time consuming. It is therefore essential to be able to determine if a plan hae been effective in achieving its objectives. When the objectives of a management plan have been achieved (for example F, has been reduced to below some threshold level) it is important to determine if it was as a direct result of elements of the plan (for example, TAC restricting fishing mortality) or because of an external factor that was not included or considered by the plan (for example, fuel price rises causing a reduction in fishing effort). In the former case, we want to be able to understand which aspects of a management plan were effective so they can be considered in the design for future plans. In the latter case, there is the possibilty of falsely attributing success to aspects of a plan that had no impact, thereby needlessly including them in the design of future plans. These issues can become more complicated in mixed fisheries were multiple gear types catch multiple stocks because interactions between the different biological and economic elements are not straightforward.

To allow the evaluation of fisheries management plans it is necessary to develop and test biological and economic indicators. In this study we investigate potential indicators for evaluating the impact of management measures on the dynamics fisheries and stocks subject to management plans. One approach of doing this is to look at the relationships between a range of biological, economic and management variables from a selection of stocks and fleets in the area. We expect many relationships in fisheries to be non-linear (for example, those between fishing effort and fishing mortality). Distance correlation is more useful than standard correlation for detecting non-linear associations between variables, particularly in terms of avoiding both Type I and Type II errors and so distance correlation should be preferred to standard correlation for investigating these relationships.

We go on to apply to these methods using sole in the Western Channel mixed fishery as a case study. Further analyses will be possible by linking economic and landings data through transversal variables. For example, it will be interesting to investigate the associations between effort, variables costs and fishing mortality of the larger vessels, the reduction of which has been suggested as a key factor in the decrease of fishing mortality on sole.

2 Introduction

Developing and implementing management plans of fisheries can be costly and time consuming. It is therefore very important to evaluate whether or not these plans actually have the desired impact on the performance of the fishery. Managers are eager to claim credit when fisheries perform successfully, for example, if a stock recovers or a fishery becomes profitable. However, when fisheries do not perform successfully, the reasons for the performance are often attributed to external factors that were not possible to manage, e.g. environmental factors or changes in the economic change.

Proposed fisheries management plan are evaluated before they are adopted. This is often done using computer simulations that evaluate the performance of the proposed plan over a range of scenarios. However, due to the high levels of uncertainty in fisheries systems, it is not possible for these evaluations to account for every possible future event. Consequently, fisheries may be exposed to a range of factors that were not considered in the plan evaluations. Some of these factors can have unexpected positive impacts on the fishery which cannot be attributed to deliberate management.

For example, North Sea plaice endured decades of high fishing pressure that lead to a decline in the stock. A management plan was introduced with the intention of reducing fishing mortality. Recent reductions in fishing mortality mean that fishing mortality is now at around Fmsy. However, it is thought that the reason that fishing mortality declined is because effort substantially declined for a number of reasons including oil prices (ICES, 2014b). It is not possible to attribute the decline in fishing mortality to within safe limits to deliberate management alone.

Another example is Sole in the South West (Division VIIe) where fishing mortality has recently declined to within safe limits after decades of high exploitiation. It is thought that a UK decommissioning scheme led to the decline of 24m boats in favour of smaller boats and also the substantial increases in fuel costs making larger boats commerially unviable (ICES, 2014a). Again, the decline in fishing mortality can not be attributed to active management.

The biological dynamics of a stock is something that management has very little control over but that can have a large impact on the performance of the fishery. For example, cod in the Celtic Sea (Division VIIe-k) has been over-exploited for decades leading to a decline in the stock abundance. However, in 2010 there was a large, seemingly random recruitment event which may allow the stock to recover with appropriate management (ICES, 2014a). This recruitment event had nothing to do with any management plan for the stock, but it will require careful managment to take advantage of it.

There has been a lot of work on how to evaluate the potential effectiveness of a proposed managent plan and whether it will be robust to a range of uncertainties (e.g. Management Strategy Evaluation, Kell et al. (2007)). However, there has been comparatively little research on methods of post-hoc analyses to evaluate if a plan actually had an impact on the performance of the fishery. Here we look at answering the question: can the impact of management measures on stock dynamics be detected? To do this we investigate the use of a new correlation method (distance correlation) that can be used to detect dependence between non-linearly related variables. We then apply this method to a case study: sole in the Division VIIe (part of a mixed fishery).

3 Detecting relationships between variables

Many methods are available to quantify the strength of association between a pair of variables. The most familiar method is correlation. However, correlation is only for quantifying the strength of a linear relationship. In the real world, most relationships are non-linear and are only approximately linear over a small range meaning that correlation must be used with care. For example, the recent relationship between fishing effort and fishing mortality for sole in Division in VIIe is thought to be non-linear as vessels have been fishing further south (ICES, 2014a).

A proposed alternative method for quantifying association is the Maximal Information Coeffecient (Reshef et al., 2011). However, serious limitations with this method have been identified (Simon and Tibshirani, 2014). Pattern recognition and machine learning methods are powerful (such as Dynamic Bayesian Networks and Probabilistic Graphical Models, see Airoldi (2007); Ghahramani (1998)) but these require more data than is typically available in fisheries. Here we focus on a new method, distance correlation (Szkely and Rizzo, 2009).

It must be remembered throughout this study that *correlation does not imply causation.*

4 Exploring distance correlation

Distance correlation is a measure of statistical dependence between two random variables or two random vectors of arbitrary, not necessarily equal dimension. An important property is that this measure of dependence is zero if and only if the random variables are statistically independent (Szkely and Rizzo,

2009). This is different to standard correlation where a correlation of zero does not imply independence. Distance correlation is implemented in the R package *energy* (Rizzo and Szekely, 2014).

4.1 Simple examples of dcor versus correlation

To demonstrate distance correlation, eight functions with noise are evaluated with random independent data: linear, parabolic, cubic, two sine functions, power, circle and a step (following the example in `http://www-stat.stanford.edu/~tibs/reshef/script.R`). Distance correlation and standard correlation scores and p-values are then calculated.

```
rm(list=ls())
library("energy")
library("reshape2")
library("plyr")
library("ggplot2")
library(corrplot)
```

```
linear <- function(x, noise_gain){
    y <- x + noise_gain * rnorm(length(x))
    return(y)
}
parabolic <- function(x, noise_gain){
    y <- 4*(x-0.5)^2+  noise_gain * rnorm(length(x))
    return(y)
}
step <- function(x, noise_gain){
    y = (x > 0.5) + noise_gain*5 * rnorm(length(x))
    return(y)
}
circle <- function(x, noise_gain){
    y <- (2*rbinom(length(x),1,0.5)-1) * (sqrt(1 - (2*x - 1)^2)) +
        noise_gain / 4 * rnorm(length(x))
    return(y)
}
cubic <- function(x, noise_gain){
    y <- 128*(x-1/3)^3-48*(x-1/3)^3-12*(x-1/3)+10* noise_gain *rnorm(length(x))
    return(y)
}
sin4 <- function(x, noise_gain){
    y <- sin(4*pi*x) + 2*noise_gain * rnorm(length(x))
    return(y)
}
sin16 <- function(x, noise_gain){
    y <- sin(16*pi*x) + 2*noise_gain * rnorm(length(x))
    return(y)
}
power4 <- function(x, noise_gain){
    y <- x^(1/4) + noise_gain * rnorm(length(x))
    return(y)
}
```

```
set.seed(1)
max_length <- 100
noise_gain <- 0.1
scenario_names <- c("linear","parabolic","cubic","sin4","sin16","power4",
```

```
    "circle","step")
no_scenarios <- length(scenario_names)
# Independent and dependent data
x <- runif(max_length, min=0,max=1)
y <- array(NA,dim=c(no_scenarios, max_length), dimnames=list(scenario =
    scenario_names, 1:max_length))
# For deterministic results
det_x <- seq(from = 0, to = 1, length = 1000)
det_y <- array(NA,dim=c(no_scenarios,length(det_x)), dimnames = list(scenario =
    scenario_names, 1:length(det_x)))
for (scenario in scenario_names){
    # Stochastic ones
    y[scenario,] <- do.call(scenario, list(x=x, noise_gain=noise_gain))
    # And the deterministic ones
    det_y[scenario,] <- do.call(scenario, list(x=det_x, noise_gain=0))
}
```

Examples of the eight functions, along with the correlation scores can be seen in Figure 1. It is clear that standard correlation is much poorer at detecting non-linear relationships than distance correlation.

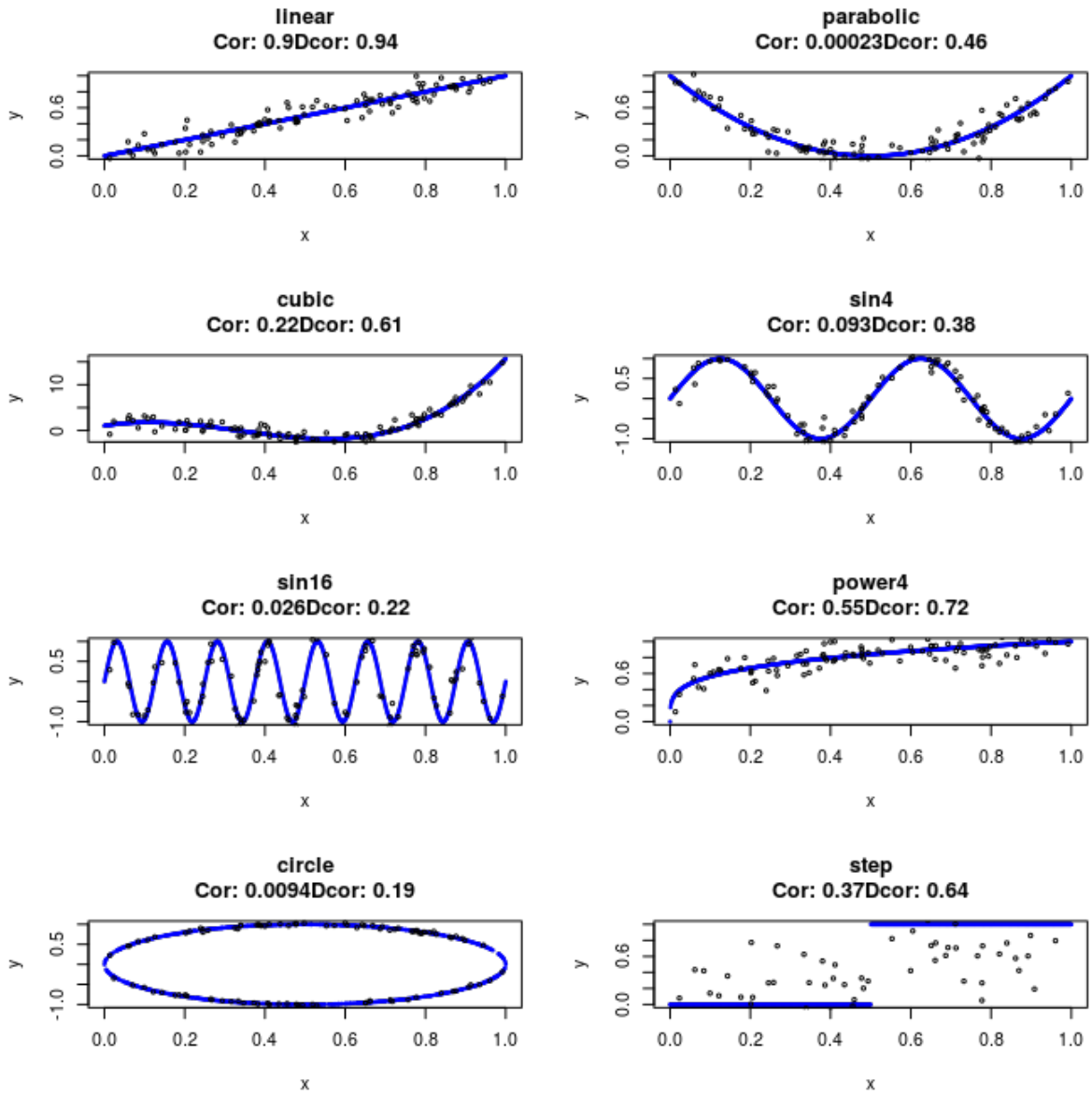

Figure 1: Examples of the eight functions with standard and distance correlation scores. Distance correlation satisfies 0 <= R <= 1, and R = 0 only if X and Y are independent.

4.2 Power of distance correlation

Power analysis is an important aspect of experimental design. It allows the requied sample size to detect an effect of a given size with a given degree of confidence to be determined. Conversely, it allows the probability of detecting an effect of a given size with a given level of confidence, under sample size constraints, to be determined. If the probability is unacceptably low, it would be wise to alter or abandon the experiment.

The power of a statistical test is the probability that the test will reject the null hypothesis when the alternative hypothesis is true (i.e. the probability of not committing a Type II error). That is:

statistical power = P(we reject the null hypothesis | the null hypothesis is false)

Here, the null hypothesis is that the data sets are independent, i.e. distance correlation should be 0.

In this section we test the power of distance correlation and correlation. The procedure is as follows:

- Generate 500 sets of random X1
- Calculate Y1, Y2, ... Y8 for each set of random X1 using the 8 functions
- Generate a new X (one not used to calculate Y) and correlate X with Yi. This is the null scenatio - i.e. correlating Yi with a vector that did not generate Yi (independence - there should be no correlation)
- Generate 500 sets of random X2
- Calculate Y1, Y2, ... Y8 for each random X2 using the 8 functions
- Correlate X2 with Yi. This is the alternative scenario - correlating Y with X that did generate Y (dependence)

Power is then calculated as follows:

- Get the 95% quantile of the null scenario correlations. We expect this to be low as they are independent.
- Calculate the proportion of the alternative scenario correlations that are greater than this i.e. what is the probability that the correlation coefficient from the alternative (dependence) scenario is higher than the null (independence) scenario (with 95% confidence).

We calculate the power for a range of sample sizes and noise levels.

```
set.seed(0)
max_length <- 100
min_length <- 10
lengths <- seq(from = min_length, to = max_length, by = 10)
noise_gain <- seq(from = 0.05, to = 0.2, by = 0.05)
no_sets <- 500
# Objects to store the results
dcor_null <- array(NA, dim = c(length(lengths), length(noise_gain),
    no_sets, no_scenarios),
    dimnames = list(length = lengths, noise_gain = noise_gain,
        set=1:no_sets, scenario = scenario_names))
cor_null <- dcor_null
dcor_alt <- dcor_null
cor_alt <- dcor_null
pvalue_alt <- dcor_null
pvalue_null <- dcor_null
# Get y1, the null scenario
for (length_counter in 1:length(lengths)){
    for (noise_counter in 1:length(noise_gain)){
        for (set_counter in 1:no_sets){
            x1 <- runif(lengths[length_counter], min=0,max=1)
            x2 <- runif(lengths[length_counter], min=0,max=1)
            for (scenario in scenario_names){
                y1 <- do.call(scenario, list(x=x1,
                    noise_gain=noise_gain[noise_counter]))
                y2 <- do.call(scenario, list(x=x2,
                    noise_gain=noise_gain[noise_counter]))
                # Get dcor, cor and pvalues
                # Square the correlations to make them comparable
                dcor_null[length_counter, noise_counter, set_counter, scenario] <-
                    dcor(x=x2, y=y1) # Null - x2 did not generate y1
                cor_null[length_counter, noise_counter, set_counter, scenario] <-
                    cor(x=x2, y=y1)^2 # Null - x2 did not generate y1
                dcor_alt[length_counter, noise_counter, set_counter, scenario] <-
```

```
                    dcor(x=x2, y=y2) # Alt - x2 did generate y2
                cor_alt[length_counter, noise_counter, set_counter, scenario] <-
                    cor(x=x2, y=y2)^2 # Alt - x2 did generate y2
                pvalue_alt[length_counter, noise_counter, set_counter, scenario] <-
                    dcov.test(x=x2,y=y2)$p.value
                pvalue_null[length_counter, noise_counter, set_counter, scenario] <-
                    dcov.test(x=x2,y=y1)$p.value
            }
        }
    }
}
```

```
# Melt them down for easy analysis
dcam <- melt(dcor_alt)
dcnm <- melt(dcor_null)
cam <- melt(cor_alt)
cnm <- melt(cor_null)
# Get 95% quantiles of the null hypothesis by scenario, noise level and length
dcnq95 <- ddply(dcnm, .(length, noise_gain, scenario), summarise,
    q95 = quantile(value, probs=0.95))
cnq95 <- ddply(cnm, .(length, noise_gain, scenario), summarise,
    q95 = quantile(value, probs=0.95))
# Power is proportion of alternative scenarios that are greater than this (at 95%)
dcam <- join(dcam, dcnq95)
cam <- join(cam, cnq95)
dcpower <- ddply(dcam, .(length, noise_gain, scenario), summarise,
    power = sum(value > q95) / length(value))
cpower <- ddply(cam, .(length, noise_gain, scenario), summarise,
    power = sum(value > q95) / length(value))
```

Distance correlation has high power for all functional relationships except circular and high frequency sinusoidal relationships (sin16), where it is still better than correlation (Figure 2). For low frequency sinusoidal and cubic relationship, distance correlation has consistently better power than correlation for all lengths and noise levels. The biggest difference between using distance correlation and standard correlation is with the parabolic relationship, where the power of standard correlation is extremely weak. For the linear, power4 and step relationships the difference in power between the two methods is small (power4 is fairly linear looking over the range of x values, and the step relationship lends itself to a linear fit from low to high). However, that is not to say that they give similar correlation scores. We are looking at the power of the two methods to distinguish between independent and dependent relationships. For example, with the step relationship the distance correlation is always higher than correlation. As expected, as length increases and noise decreases, the power improves.

```
p <- ggplot(dcpower) +
geom_line(aes(x=length, y=power, group = noise_gain, colour=noise_gain)) +
    facet_wrap(~scenario, ncol = 2)
p + geom_line(aes(x=length, y=power, group = noise_gain,
    colour=noise_gain), linetype=2, data = cpower)
```

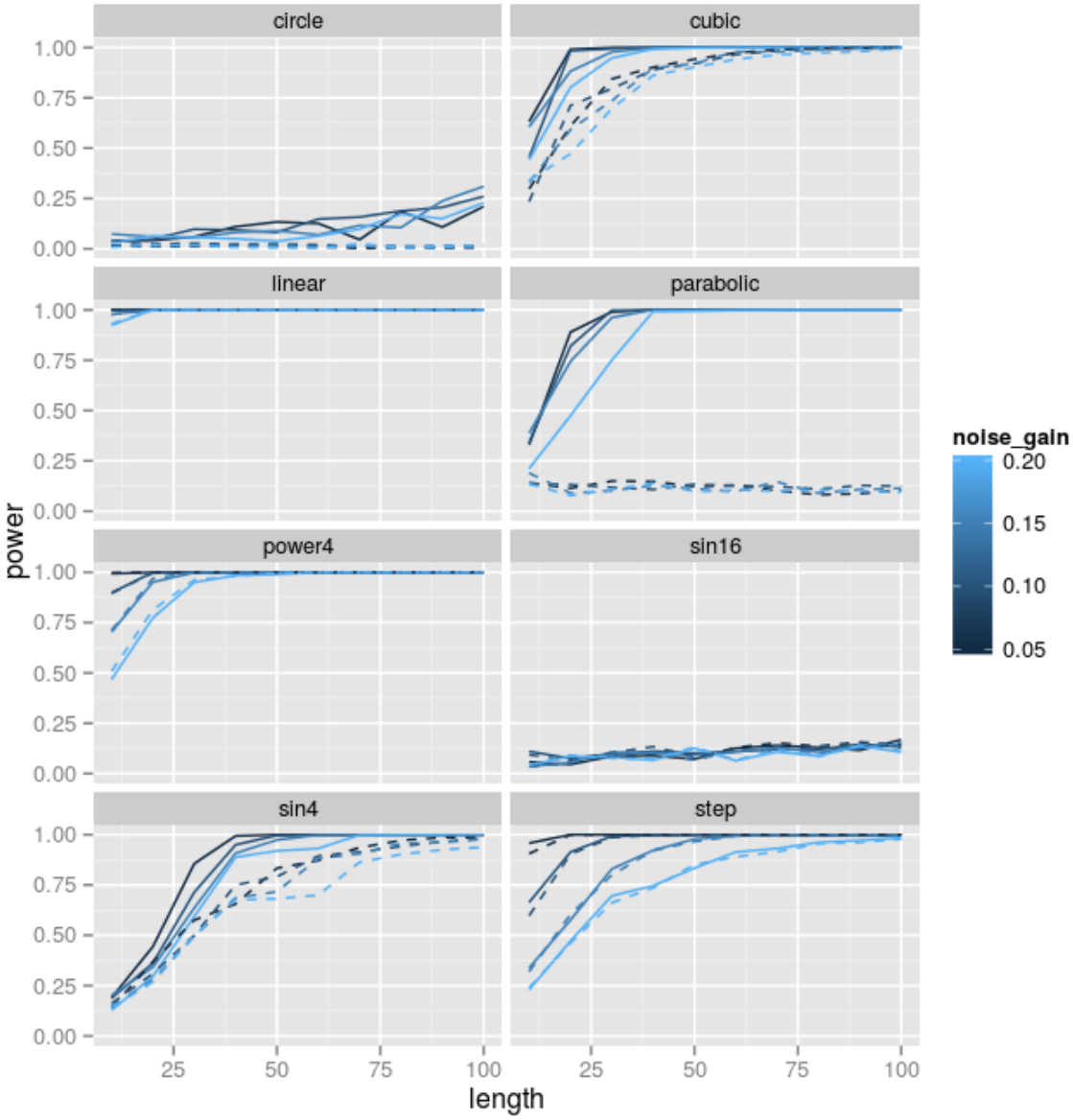

Figure 2: Power (at 95%) of correlation (dashed line) and distance correlation (solid line) at detecting dependence with different data lengths and noise levels.

The above analysis shows that for non-linear relationships distance correlation has equal or more power than correlation for detecting dependence, particularly for parabolic and cubic relationships. This is a very attractive property suggesting that distance correlation should be preferred over correlation, particularly when investigating non-linear relationships.

4.3 Significance tests

We saw above that the power of distance correlation is enough to avoid Type II errors for many relationship types. However, it is possible that the distance correlation score between two independent data sets can be greater than 0, implying dependence i.e. the chance of a Type I error (a false positive). The *dcov.test()* function provides a test of multivariate independence using a permutation bootstrap method. It returns a p-value that can be used for significance testing. Performing this test will help avoid Type I errors i.e. avoid mistakenly rejecting the null (independence) hypothesis.

In the power analysis above we also calculated the p-values from performing distance correlation and standard correlation on the dependent (*pvalue_alt*) and independent (*pvalue_null*) data.This p-value should

help us determine if the distance correlation score is 'reliable', i.e. if a score greater than 0 is found (implying dependence) can we believe it?

```
palt <- melt(pvalue_alt)
names(palt)[names(palt)=="value"] <- "pvalue"
pnull <- melt(pvalue_null)  # Hopefully showing not significant
names(pnull)[names(pnull)=="value"] <- "pvalue"
palt <- join(palt, dcam)
pnull <- join(pnull, dcnm)
pnull_prop <- ddply(pnull, .(length, noise_gain, scenario), summarise,
    prop_sig = sum(pvalue < 0.05)/length(pvalue), med_dc = median(value))
palt_prop <- ddply(palt, .(length, noise_gain, scenario), summarise,
    prop_sig = sum(pvalue < 0.05)/length(pvalue), med_dc = median(value))
p_props <- rbind(cbind(data = "indep",pnull_prop),cbind(data = "dep",palt_prop))
```

Here we use a significance value of 5% (i.e. if two vectors have a distance correlation p-value less than 0.05 we reject the null hypothesis of independence). For distance correlation to be useful we want to avoid scenarios where a high distance correlation score for independent vectors is also significant (a p-value < 0.05). We calculate the proportion of iterations wich have a p-value < 0.05, i.e. the proportion of iterations for which we reject the null hypothesis of independence and are therefore considered to be dependent (Figure 3).

When using distance correlation on the independent vectors, only 4.6% of all 500 sets across all functional relationships, lengths and noise gains are incorrectly identified as dependent (at a significent level of 0.05). With the dependent vectors, this increases to 71%. These percentages do not not consider what the actual correlation score is, and ignore the impact of length of data set, functional relationship and noise level.

The independent data always have a low proportion of significant iterations. This demonstrates that we can avoid Type I errors (i.e. claiming that the data are dependent, when they are not). Even when the data are incorrectly identified as dependent, the distance correlation scores are low. The proportion of significant iterations for the dependent data is generally higher but depends on the scenario and the length of data (the impact of noise not shown but the proportion increases as the noise level decreases). The functional relationships that are most difficult to detect are circular and high frequency sinusoidal. Not only do these have low median scores but the relationship is not often found to be significant. The other relationships combine high scores that are often found to be significent. The more data present, the higher the proportion of signifiant results.

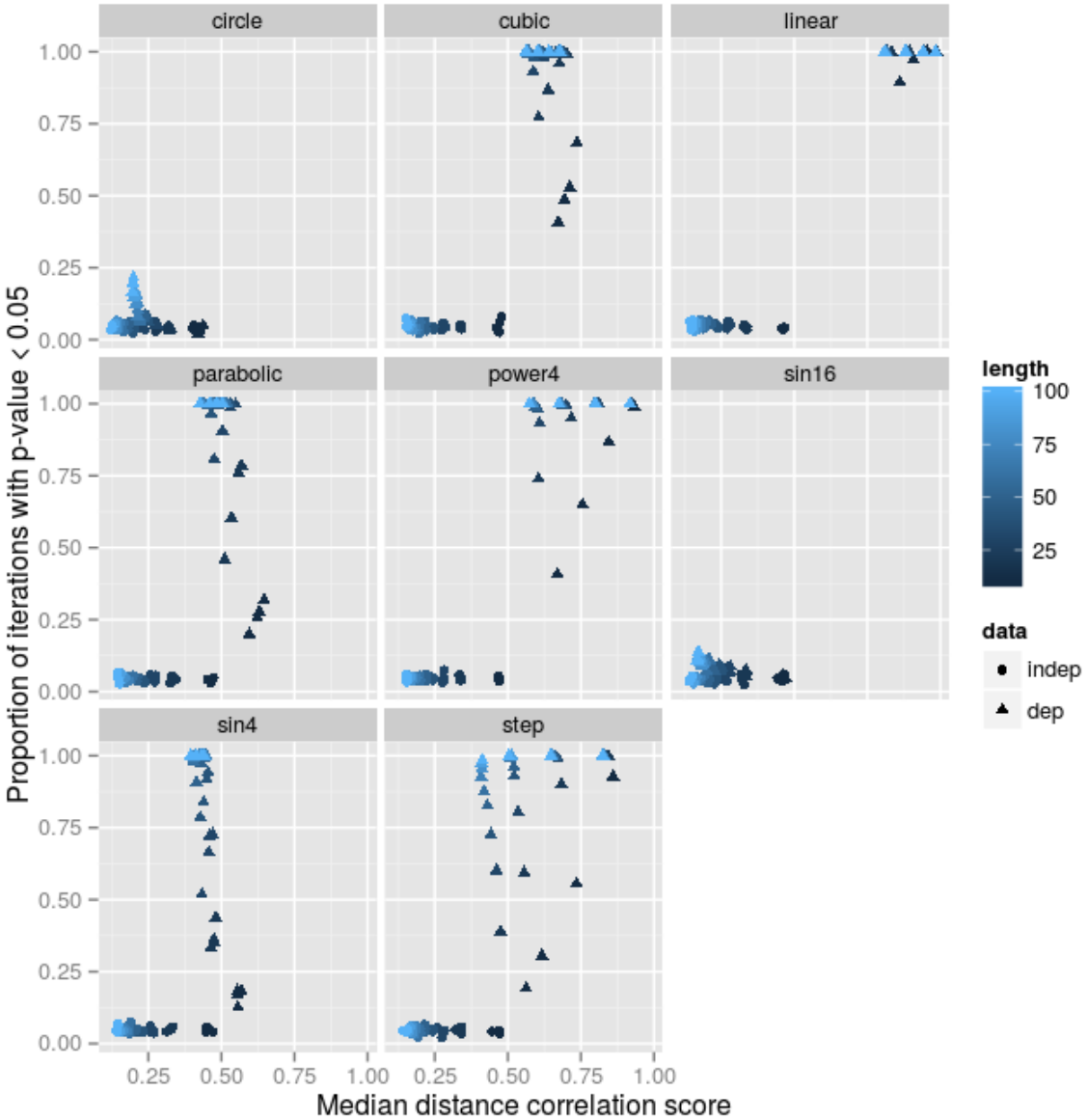

Figure 3: Proportion of iterations with p-value < 0.05, i.e. the proportion of iterations for which we reject the null hypothesis of independence and are therefore considered to be dependent. The independent data (circles) always has a low proportion of significant iterations. The proportion for the dependent data (triangles) is generally higher but depends on the scenario and the length of data (impact of noise not shown but the proportion increases as the noise level decreases).

We can see the impact of noise by looking in detail at the parabolic relationship (Figure 4). Short time series suffer from a relatively low level of significant iterations, even with low levels of noise. This means that with short time series there is a chance that dependent time series will be mistakenly classified as independent. This is an issue with fisheries data because we are generally dealing with short time series. Additionally, if we are trying to evaluate the impact of a management plan, we cannot do so with this method until many years have passed (if the relationship is strongly not linear, e.g. parabolic).

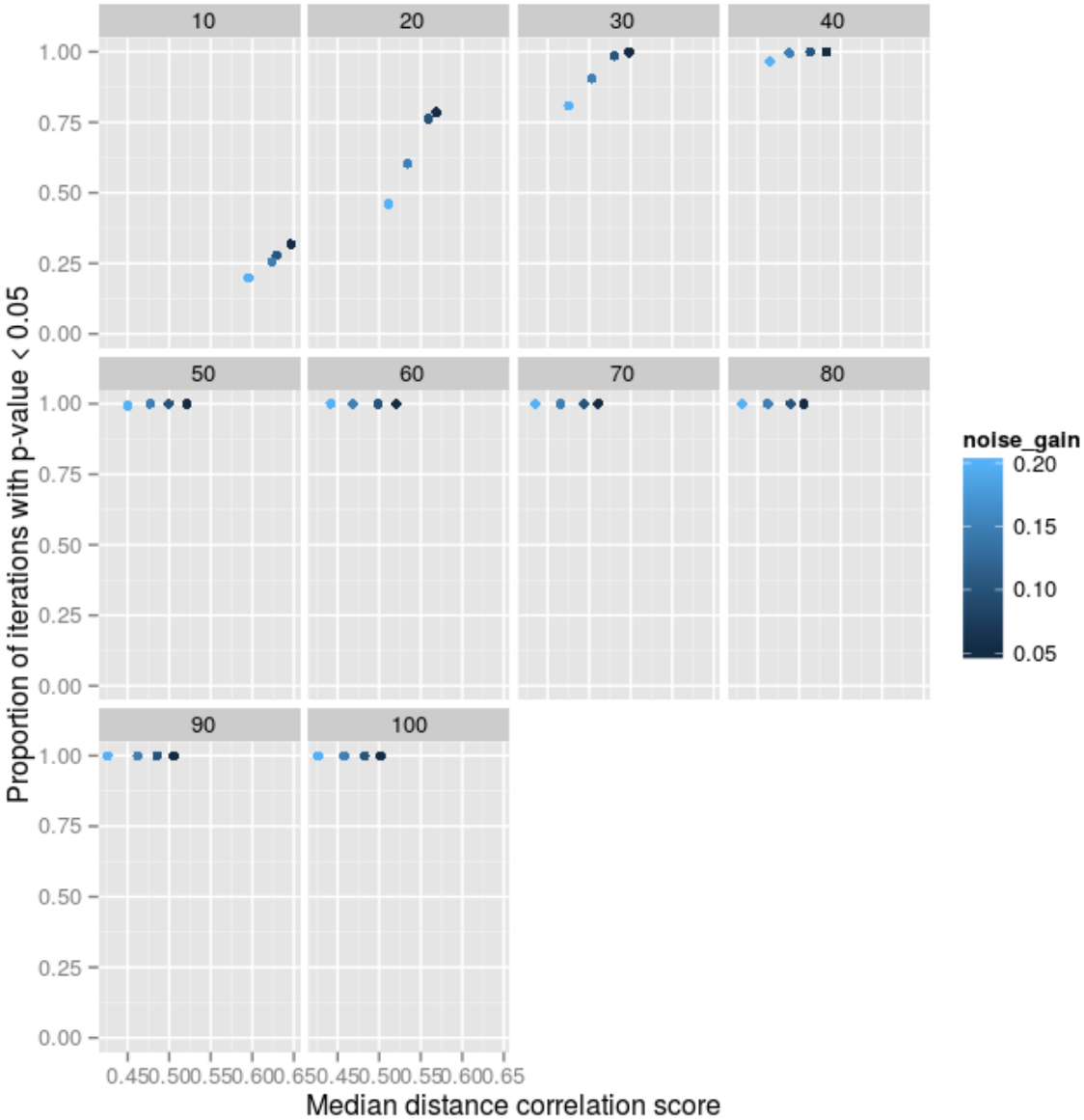

Figure 4: Proportion of iterations with p-value < 0.05 for the 'parabolic' relationship and the dependent data only. Each panel has a longer data series. As the data length and noise level increase so does the proportion of significant iterations.

5 Case study - Sole in Division VIIe (Western Channel)

5.1 Introduction

Western Channel sole is part of a mixed fishery where sole only makes up a part of the catches of the fleets. It is caught predominantly by beam trawls, gill nets and otter trawls. The multi-annual plan for the management of Western Channel sole (Regulation EC 509/2007) commenced in 2007 and was first reviewed in 2010. The plan is a mixture of TAC and effort control for some gears. Only beam trawlers and static gears (mainly gill nets) are under effort regulation. Otter trawl fleets (mainly French) are currently not restricted by effort. Beam trawlers represent the largest component of catches (on average 64% from 2010 to 2012) with French trawlers (otter and dredge) taking most of the remainder.

A recent evaluation of the plan found that F is now below the target value of 0.27 despite landings exceeding the TAC. The evaluation also found that the major reduction in fishing mortality is caused by

the reduction in catches of sole by the UK beam trawl fleet as a consequence of a reduction in effort in conjunction with a spatial change in the distribution to areas of lower sole catches. This reduction in effort of the UK beam trawl fleet is a result of a decommissioning scheme that led to the decline of 24m boats in favour of smaller boats and also the substantial increases in fuel costs that made larger boats commercially unviable. Effort and vessel numbers have reduced in most of the other fleets fishing in VIIe. However, it is unlikely that the observed reduction in kW days and vessel numbers has been in response to the plan. For example, the decrease in effort for the French fleet is mainly due to a decrease in the number of bottom trawlers fishing in VIIe. The evaluation concluded that the majority of fishing effort deployed in the Western Channel is effort that is not being regulated by the management plan for sole and that the TAC restriction is the major management measure currently restricting catches of sole in the area and is the only effective element of the plan (STECF, 2014).

However, it can be argued that fishing mortality only decreased because of the UK decommissioning scheme. Therefore, can the decline in fishing mortality really be attributed to the management plan, or is it just a 'happy accident'?

In this section we look at the dynamics of sole and other species in the Western Channel and in surrounding waters (Celtic Sea and Eastern Channel) and investigate possible relationships.

5.2 Data and correlations

We take data from the most recent ICES assessments including catches, landings, discards, fishing mortality, SSB, recruitment and TAC. We also include the price of crude oil (as a proxy for fuel costs, a variable cost) and the price of sole.

First we load in the ICES data:

```
# Read in ICES data
ices <- read.csv("../data/ICESdata/ICESStockAssessmentGraphs_20141027.csv")
# Chop out columns we don't want
cols <- c(3,4,10,13,16,18,20,21,26)
# Keep stocks we want
stks <- c("cod-7e-k","had-7b-k","ple-celt","ple-eche","ple-echw","sol-celt",
    "sol-eche","sol-echw","whg-7e-k")
dat <- ices[ices$FishStock %in% stks, cols]
colnames(dat)[colnames(dat)%in% c("FishStock")] <- c("Stock")
# Correct Catches / Discards for stocks
# sol-echw - Discarding is negligible
dat[dat$Stock=="sol-echw","Catches"] <- dat[dat$Stock=="sol-echw","Landings"]
dat[dat$Stock=="sol-echw","Discards"] <- 0
# sol-eche - Discards were assumed to be negligible prior to this assessment
# preliminary information indicates discards in the region of 10% (2011-2013)
# but if we apply for all years - no impact on correlation, so ignore
dat[dat$Stock=="sol-eche","Catches"] <- dat[dat$Stock=="sol-eche","Landings"]
dat[dat$Stock=="sol-eche","Discards"] <- 0
# sol-celt -Discards are considered negligible. 2-5% ignore
dat[dat$Stock=="sol-celt","Catches"] <- dat[dat$Stock=="sol-celt","Landings"]
dat[dat$Stock=="sol-celt","Discards"] <- 0
# ple-eche -a large number of undersized plaice are discarded
# Discards are known to take place but are not fully quantified.
# (In the last 3 years discards were in the order of 30-40%).
# Leave C & D = NA
# ple-echw
# Discarding appears to be generally higher in quarters 1 and 2 in this fishery,
# ut is low compared to other plaice stocks (about 20%)
# Discard information available since 2012; average discard proportion 20122013
# from the majority of the fleets is 18%.
# Leave C & D = NA
# cod-7e-k
```

```
# Discards are known to take place but cannot be fully quantified for the whole
# series (in the order of 10% in recent years).
# Set C & D to NA
dat[dat$Stock=="col-7e-k","Catches"] <-NA
dat[dat$Stock=="col-7e-k","Discards"] <-NA
```

We then add the available TAC data:

```
# Add in TAC
tac <- read.csv("../data/ICESdata/TAC.csv")
# read.csv stuffs up colnames - turns - into .
colnames(tac) <- c("Year","ple-celt","ple-echw","sol-celt","sol-echw",
    "sol-iris","her-irls","sol-eche")
# Leave out irls and iris as we don't really want the Irish Sea
tac <- tac[,c(1,2,3,4,5,8)]
tac <- melt(tac, id.vars=c("Year"), variable.name="Stock")
tac <- cbind(tac,variable="TAC")
dat <- melt(dat, id.vars=c("Year","Stock"))
dat <- rbind(dat,tac)
```

We also include the price of oil (adjusted for inflation):

```
# Add in Brent price
# Adjusted for inflation:
# http://inflationdata.com/Inflation/Inflation_Rate/Historical_Oil_Prices_Table.asp
oil <- read.csv("../data/Brent.csv")
colnames(oil)[3] <- "value"
oil <- cbind(oil[,c(1,3)], Stock="Oil", variable="Price")
dat <- rbind(dat, oil)
```

Finally, we include the price of Sole and Place in the Western channel (currently there are too few years to do anything useful with):

```
# Revenue and (then) price
land.orig <- read.csv("../data/landings_by_gear.csv")
# Pull out VII e WC (and d, just to check)
wc <- land.orig[land.orig$sub_reg %in% c("27.7.d","27.7.e"),]
rm(land.orig)
# Pull out Sol and Ple
wc <- wc[wc$species_code %in% c("SOL","PLE"),]
# sum landings and revenue by species and year
wc_econ <- ddply(wc, .(year, species_code, sub_reg), summarise,
    totwghtlandg = sum(totwghtlandg,na.rm=TRUE),
    totvallandg=sum(totvallandg,na.rm=TRUE))
wc_econ$price <- wc_econ$totvallandg / wc_econ$totwghtlandg
wc_econ <- wc_econ[wc_econ$sub_reg == "27.7.e",c(1,2,4,5,6)]
wc_econ$species_code <- as.character(wc_econ$species_code)
wc_econ[wc_econ$species_code=="SOL","species_code"] <- "sol-echw"
wc_econ[wc_econ$species_code=="PLE","species_code"] <- "ple-echw"
price <- wc_econ[,c(1,2,5)]
colnames(price) <- c("Year","Stock","value")
price <- cbind(price, variable="Price")
dat <- rbind(dat,price)
```

We trim off Years >= 2014 (as only SSB and recruitment are currenly available). We also normalise the data by scaling it by the mean (this is just to make the plotting easier).

```r
# Drop out Year >= 2014 as only SSB estimates - no catches or anything
dat <- dat[dat$Year<2014,]
# Normalise time series - scale by mean
dat <- ddply(dat, .(Stock,variable), transform, value = value / mean(value, na.rm=TRUE))
```

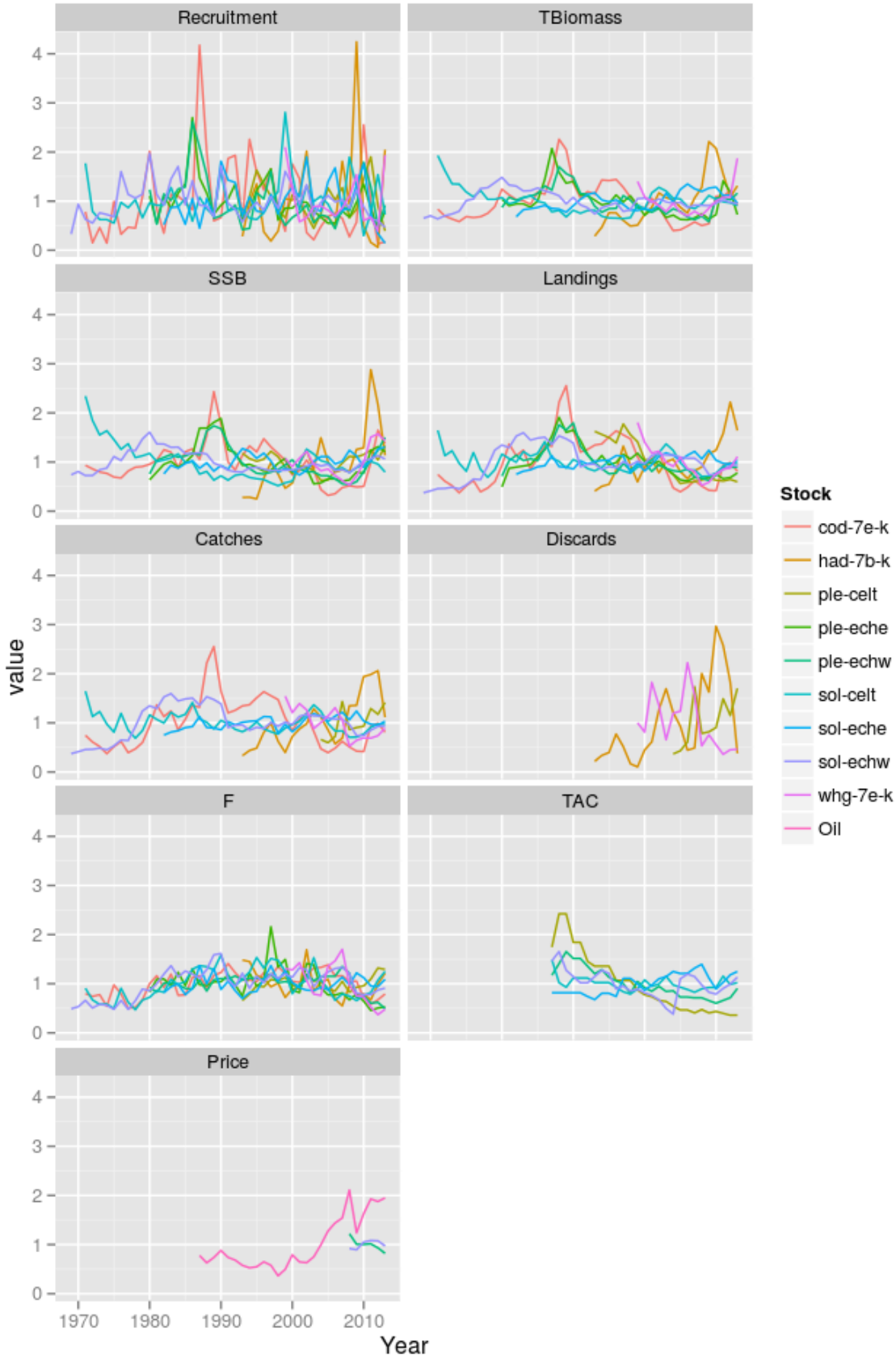

Figure 5: Time series of the normalised variables of each stock in the study.

As well as performing correlation and distance correlation on the normalised time series of values, we

also transform the time series in two additional ways:

- Difference between years
- Time lags (1 to 5 years)

```
dat2 <- ddply(dat, .(Stock, variable), function(x){
    diff_value <- diff(x$value)
    lag1_value <- x$value[-length(x$value)]
    lag2_value <- x$value[-c((length(x$value)-1):length(x$value))]
    lag3_value <- x$value[-c((length(x$value)-2):length(x$value))]
    lag4_value <- x$value[-c((length(x$value)-3):length(x$value))]
    lag5_value <- x$value[-c((length(x$value)-4):length(x$value))]
    diff_lag1_value <- diff_value[-length(diff_value)]
    diff_lag2_value <- diff_value[-c((length(diff_value)-1):length(diff_value))]
    diff_lag3_value <- diff_value[-c((length(diff_value)-2):length(diff_value))]
    diff_lag4_value <- diff_value[-c((length(diff_value)-3):length(diff_value))]
    diff_lag5_value <- diff_value[-c((length(diff_value)-4):length(diff_value))]
    out <- data.frame(Year = x$Year,
        diff_value = c(NA,diff_value),
        lag1_value = c(NA,lag1_value),
        lag2_value = c(NA,NA,lag2_value),
        lag3_value = c(NA,NA,NA,lag3_value),
        lag4_value = c(NA,NA,NA,NA,lag4_value),
        lag5_value = c(NA,NA,NA,NA,NA,lag5_value),
        diff_lag1_value = c(NA,NA,diff_lag1_value),
        diff_lag2_value = c(NA,NA,NA,diff_lag2_value),
        diff_lag3_value = c(NA,NA,NA,NA,diff_lag3_value),
        diff_lag4_value = c(NA,NA,NA,NA,NA,diff_lag4_value),
        diff_lag5_value = c(NA,NA,NA,NA,NA,NA,diff_lag5_value)
    )
    return(out)
})
# Get into molten form for helpfulness
dat3 <- rbind(melt(dat2, id.vars = c("Stock","variable","Year"),
                variable.name = "measure"),
              melt(dat, id.vars = c("Stock","variable","Year"),
                variable.name = "measure"))
```

5.3 Calculating correlations

Here we calculate the distance correlation, correlation and p-values for both for all combinations of all variables and stocks.

```
# Dcor and cor everything with everything else
cor_dat <- dcast(dat3, Year ~ Stock + variable + measure)


# Damn this takes forever...
# Could have halved as array is symmetric
# stock / var combinations
# Make an array to store the results
cor_names <- expand.grid(Stock = unique(dat3$Stock),
    variable = unique(dat3$variable), measure = unique(dat3$measure))
cor_names <- paste(cor_names$Stock, cor_names$variable, cor_names$measure, sep="_")
dcorvals <- array(NA, dim=c(length(cor_names), length(cor_names)),
```

```
    dimnames=list(cor_names, cor_names))
corvals <- array(NA, dim=c(length(cor_names), length(cor_names)),
    dimnames=list(cor_names, cor_names))
dcorpvals <- array(NA, dim=c(length(cor_names), length(cor_names)),
    dimnames=list(cor_names, cor_names))
corpvals <- array(NA, dim=c(length(cor_names), length(cor_names)),
    dimnames=list(cor_names, cor_names))

for (stock1 in unique(dat3$Stock)){
    cat("\n",stock1, "\n")
    for (var1 in unique(dat3$variable)){
        cat(var1, "\n")
        for (meas1 in unique(dat3$measure)){
            for (stock2 in unique(dat3$Stock)){
                cat(stock2, " ")
                for (var2 in unique(dat3$variable)){
                    for (meas2 in unique(dat3$measure)){
                        # Pull out values
                        val1 <- dat3[dat3$Stock==stock1 & dat3$variable == var1 &
                             dat3$measure== meas1,]
                        val2 <- dat3[dat3$Stock==stock2 & dat3$variable == var2 &
                             dat3$measure== meas2,]
                        # Include only the same year range
                        good_years <- val1$Year[val1$Year %in% val2$Year]
                        val1 <- val1[val1$Year %in% good_years,"value"]
                        val2 <- val2[val2$Year %in% good_years,"value"]
                        # Chop out NA, Infinite and NAN  vals
                        good_vals <- !is.na(val1) & !is.na(val2) & !is.nan(val1) &
                            !is.nan(val2) & !is.infinite(val1) & !is.infinite(val2)
                        val1 <- val1[good_vals]
                        val2 <- val2[good_vals]
                        name1 <- paste(stock1, var1, meas1, sep="_")
                        name2 <- paste(stock2, var2, meas2, sep="_")

                        # If less than 3 values - don't bother
                        if (length(val1) < 3){
                            dcorvals[name1, name2] <- 0
                            dcorpvals[name1, name2] <- NA
                            corvals[name1, name2] <- 0
                            corpvals[name1, name2] <- NA
                        }
                        # If symmetrical value is not NA, copy and don't recalculate
                        else if (!is.na(dcorvals[name2, name1])) {
                            dcorvals[name1, name2] <- dcorvals[name2, name1]
                            dcorpvals[name1, name2] <- dcorpvals[name2, name1]
                            corvals[name1, name2] <- corvals[name2, name1]
                            corpvals[name1, name2] <- corpvals[name2, name1]
                        }
                        else {
                            # Calc cors
                            dcorvals[name1, name2] <- dcor(val1, val2)
                            dcorpvals[name1, name2] <- dcov.test(val1, val2)$p.value
                            corvals[name1, name2] <- cor(val1, val2)^2
                            corpvals[name1, name2] <- cor.test(val1, val2)$p.value
                        }
                    }
                }
            }
```

```
        }
    }
}
```

Reorganise the results into a matrix shape for easy plotting

```
dc <- melt(dcorvals, varnames=c("X1","X2"))
# Split column names into useful columns
Var1 <- strsplit(as.character(dc$X1), "_")
# Get rid of NA in value
Var1 <- lapply(Var1, function(x) x[!is.na(x)])
dc$stock1 <- unlist(lapply(Var1, "[", 1))
dc$var1 <- unlist(lapply(Var1, "[", 2))
meas1 <- lapply(Var1, "[", -c(1,2))
meas1 <- lapply(meas1, function(x) paste(x,collapse="_"))
dc$meas1 <- unlist(meas1)
Var2 <- strsplit(as.character(dc$X2), "_")
# Get rid of NA in value
Var2 <- lapply(Var2, function(x) x[!is.na(x)])
dc$stock2 <- unlist(lapply(Var2, "[", 1))
dc$var2 <- unlist(lapply(Var2, "[", 2))
meas2 <- lapply(Var2, "[", -c(1,2))
meas2 <- lapply(meas2, function(x) paste(x,collapse="_"))
dc$meas2 <- unlist(meas2)
# Clean up
dc <- dc[,c("stock1","var1","meas1","stock2","var2","meas2","value")]
colnames(dc)[7] <- "dcvalue"
# pvalues has same columns so just copy in column
dcp <- melt(dcorpvals)
dc$dcpvalue <- dcp$value
# Do same for correlation
corm <- melt(corvals)
cormp <- melt(corpvals)
dc$cvalue <- corm$value
dc$cpvalue <- cormp$value
```

5.4 Western Channel sole results

In this section we look at only the results for sole in the Western Channel and check that the measures are coherent, e.g. F and Catches should not be independent.

We take a look at the time series of variables of interest first (Figure 6).

```
stk <- "sol-echw"
sol_plot <- dat3[dat3$Stock %in% c(stk) & dat3$variable %in%
    c("Catches","Price","TAC","F") & dat3$measure %in% c("diff_value","value"),]
oil_plot <- dat3[dat3$Stock %in% c("Oil") & dat3$variable %in% c("Price")
    & dat3$measure %in% c("diff_value","value"),]
sol_plot <- rbind(sol_plot,oil_plot)
sol_plot$stock_variable <- paste(sol_plot$Stock, sol_plot$variable, sep="_")
# Data for pairwise plot
sol_pair <- dcast(sol_plot[sol_plot$measure=="value",c(3,5,6)], Year ~ stock_variable)
```

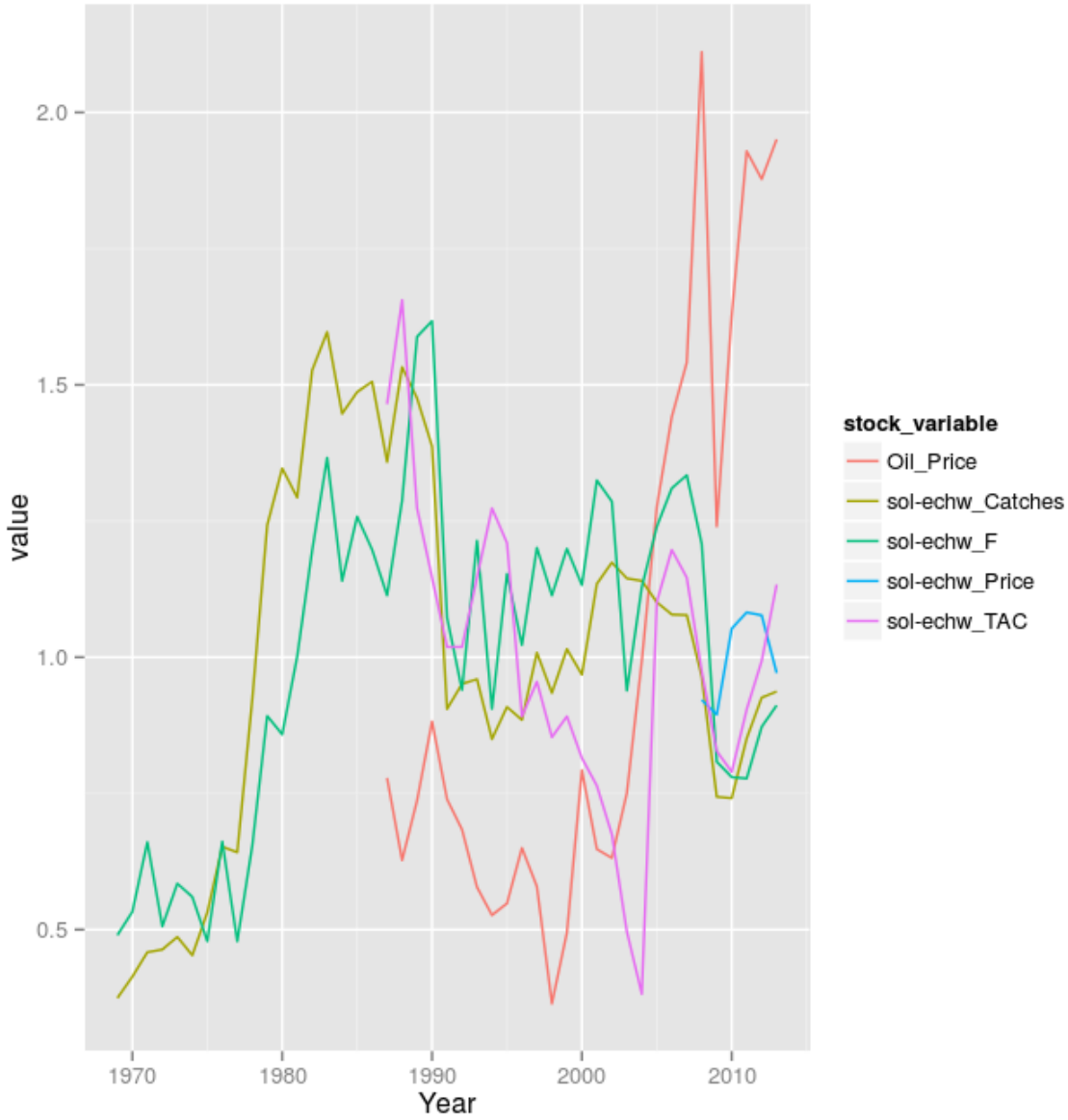

Figure 6: Time series of the normalised variables for Western Channel Sole.

We also produce pairwise plots to see how the variables are related (Figure 7). It is clear that catches and F are not independent and that catches and TAC are possibly related.

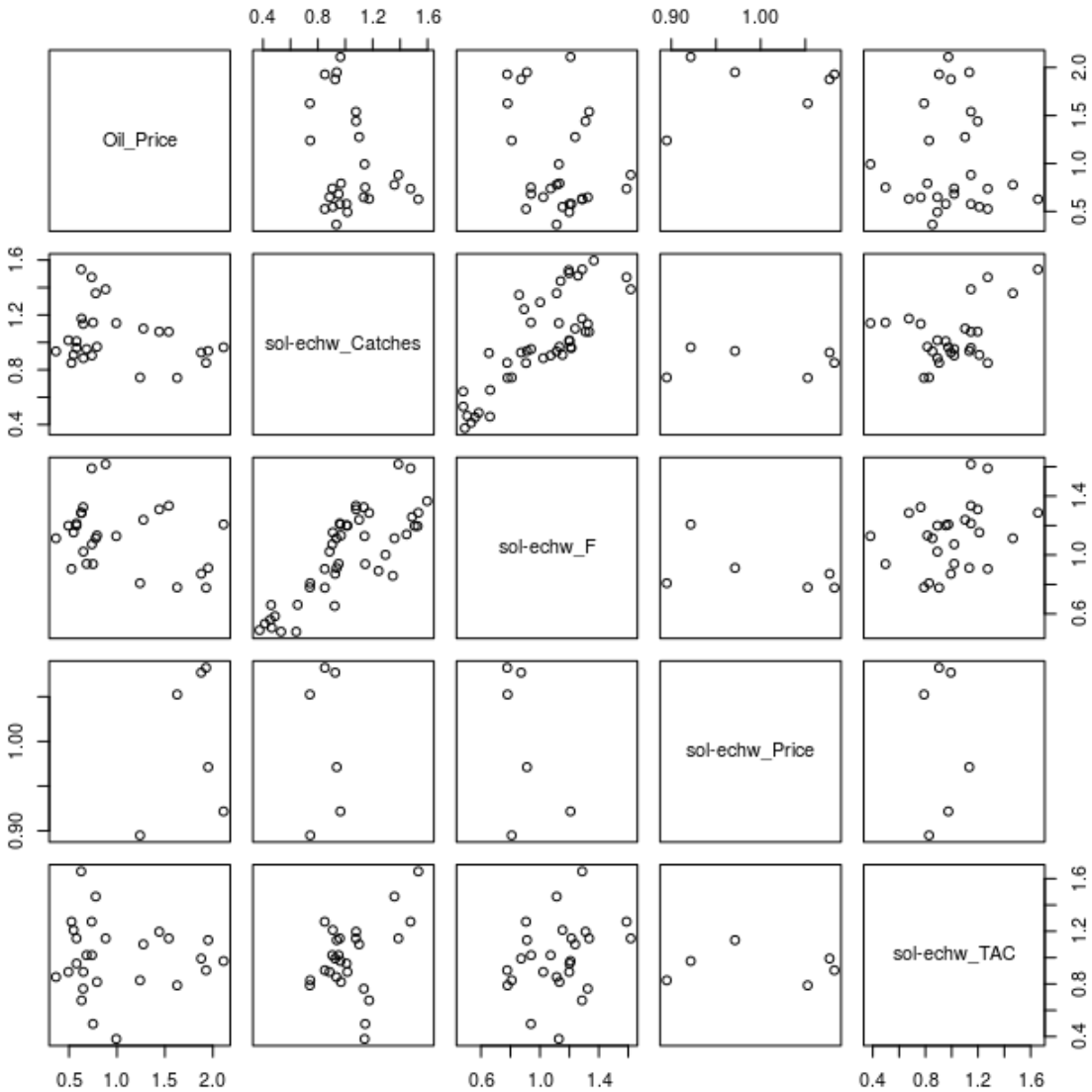

Figure 7: Pairwise plot of the normalised variables for Western Channel Sole.

We reshape the data for plotting the correlations and remove NA rows and columns:

```
sol <- dc[(dc$stock1 %in% c(stk,"Oil")) & (dc$stock2 %in% c(stk,"Oil")) &
          (dc$var1 %in% c("Catches","Price","TAC","F")) &
          (dc$var2 %in% c("Catches","Price","TAC","F")) &
          (dc$meas1 %in% c("value")) & (dc$meas2 %in% c("value")), ]

# Remove NAs
soldc <- sol[!is.na(sol$dcpvalue), c("stock1","var1","meas1","stock2","var2","meas2","dcvalue","dcpvalu
soldcv <- acast(soldc, stock1 + var1 + meas1 ~ stock2 + var2 + meas2,
    value.var = "dcvalue")
soldcp <- acast(soldc, stock1 + var1 + meas1 ~ stock2 + var2 + meas2,
    value.var = "dcpvalue")
```

We set the colour range for the correlation plots:

```
colv <- colorRampPalette(c("white","white","white","white",
                           "yellow","green","blue","red"))
```

We can plot the distance correlation matrix, only plotting the relationships which have a p-value <= 0.05, the relationships which are not independent (Figure 8). The two significant relationships (other than the diagonal) are the fishing mortality (F) and catches, and TAC and catches. That F and catches are not independent is no surprise given that F is the output from a model that fits to the catches. More interesting is that TAC and catches are not independent, suggesting that the management plan is having an effect on fishery.

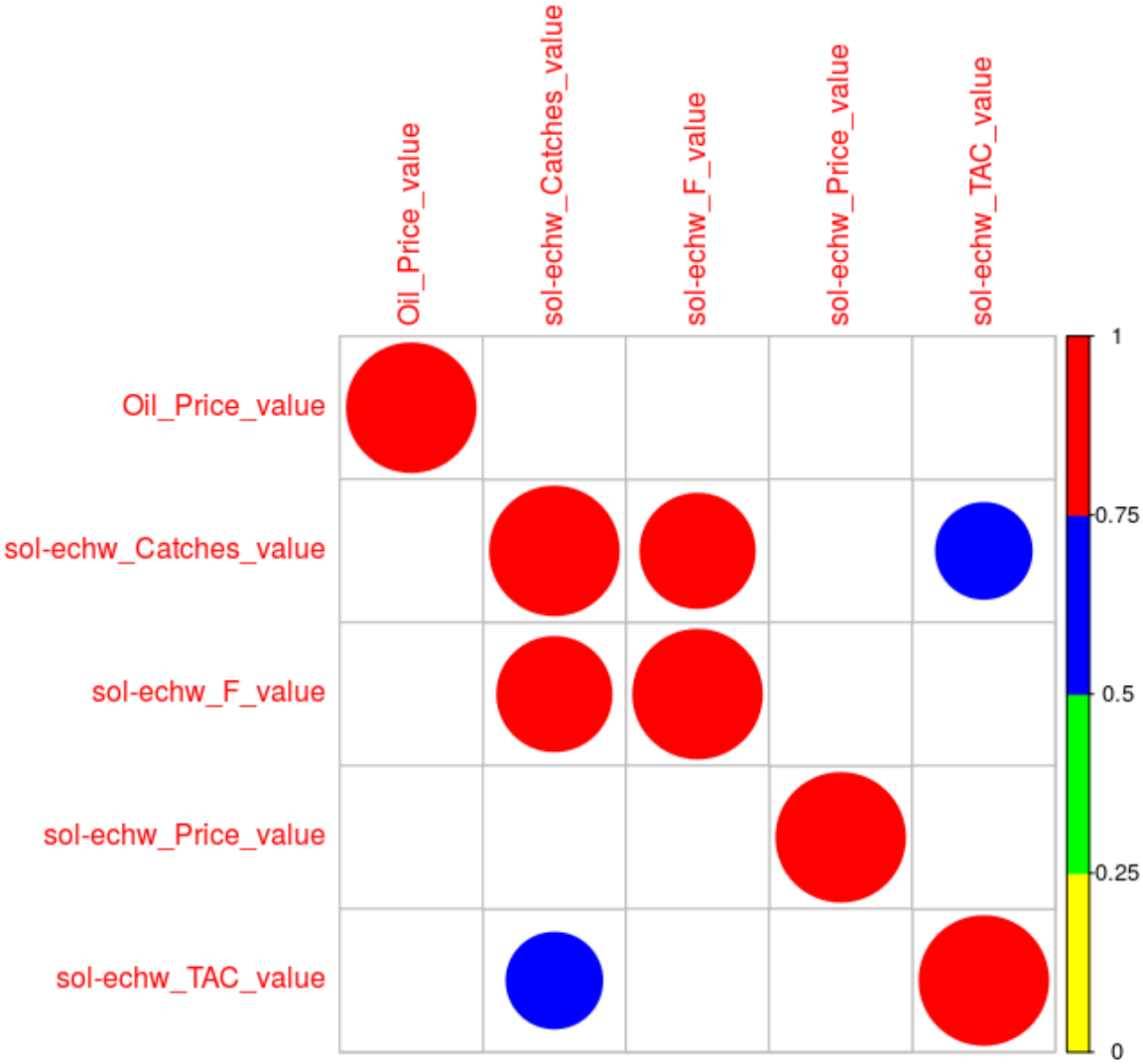

Figure 8: Distance correlation matrix for Western Channel Sole. Only significant relationships (p <= 0.05) are plotted.

5.5 TAC and catches for all species

In this section we look at the relationship between TAC and catches for all sole and plaice stocks in the Western and Eastern Channels and in the Celtic Sea.

```
tac <- dc[!(dc$stock1 %in% c("Oil","cod-7e-k","had-7b-k","whg-7e-k")) &
          !(dc$stock2 %in% c("Oil","cod-7e-k","had-7b-k","whg-7e-k")) &
          (dc$var1 %in% c("Catches","TAC")) & (dc$var2 %in% c("Catches","TAC")) &
          (dc$meas1 %in% c("value")) & (dc$meas2 %in% c("value")), ]
# Get data for time series plot
tac_plot <- dat3[!(dat3$Stock %in% c("Oil","cod-7e-k","had-7b-k","whg-7e-k")) &
             dat3$variable %in% c("Catches","TAC") & dat3$measure %in% c("value"),]
tac_plot$stock_variable <- paste(tac_plot$Stock, tac_plot$variable,sep="_")
# Data for pairwise plot
tac_pair <- dcast(tac_plot[,c(3,5,6)], Year ~ stock_variable)
# remove NA columns (ple-eche and ple-echw catches - unknown discards
tac_pair <- tac_pair[,!(apply(tac_pair, 2, function(x) all(is.na(x))))]
```

The normalised catches and TACs can be seen in Figure 9.

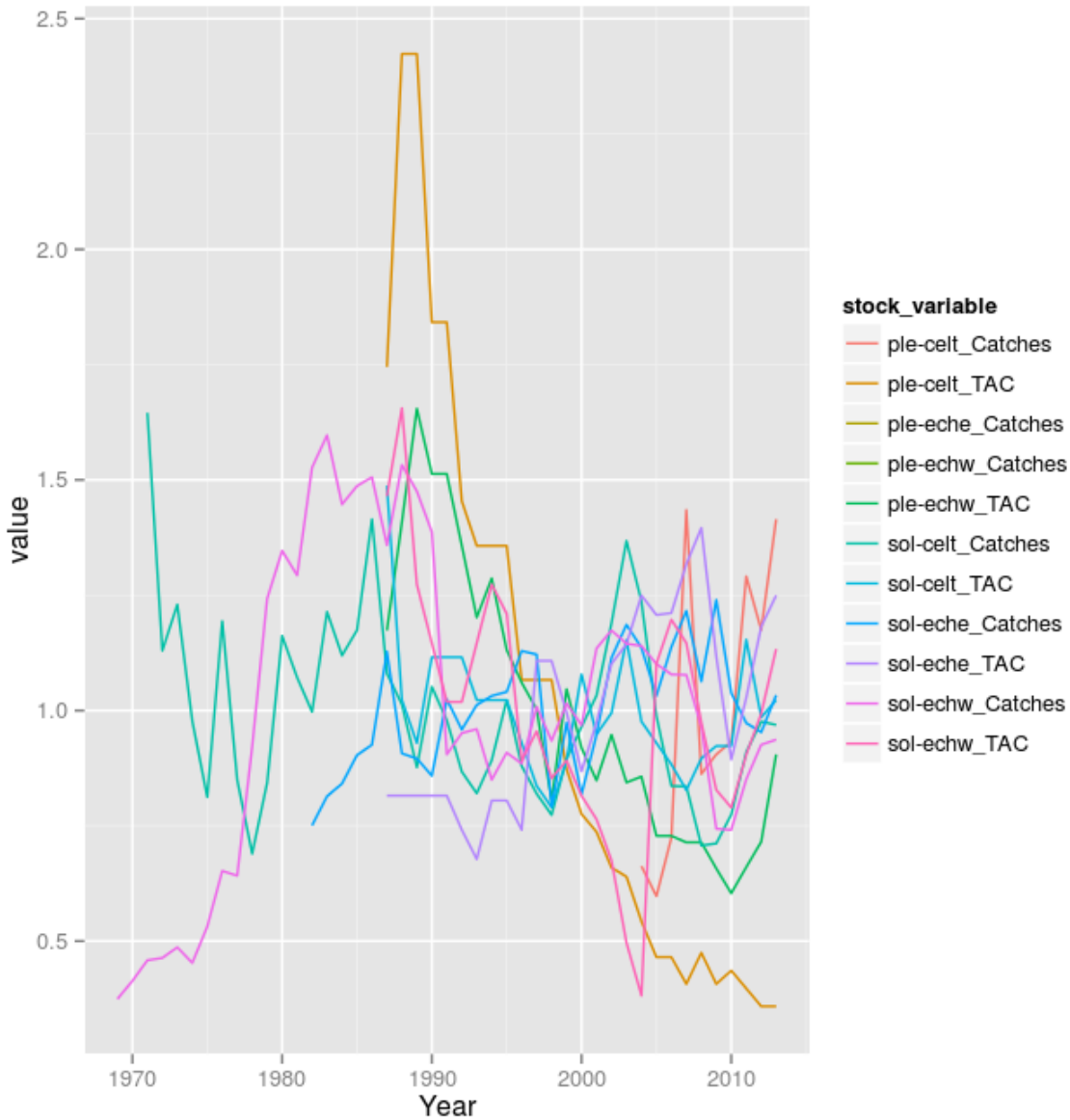

Figure 9: Time series of catches and TAC (where available) for all species.

A pairwise plot of the normalised data can be seen in Figure 10.

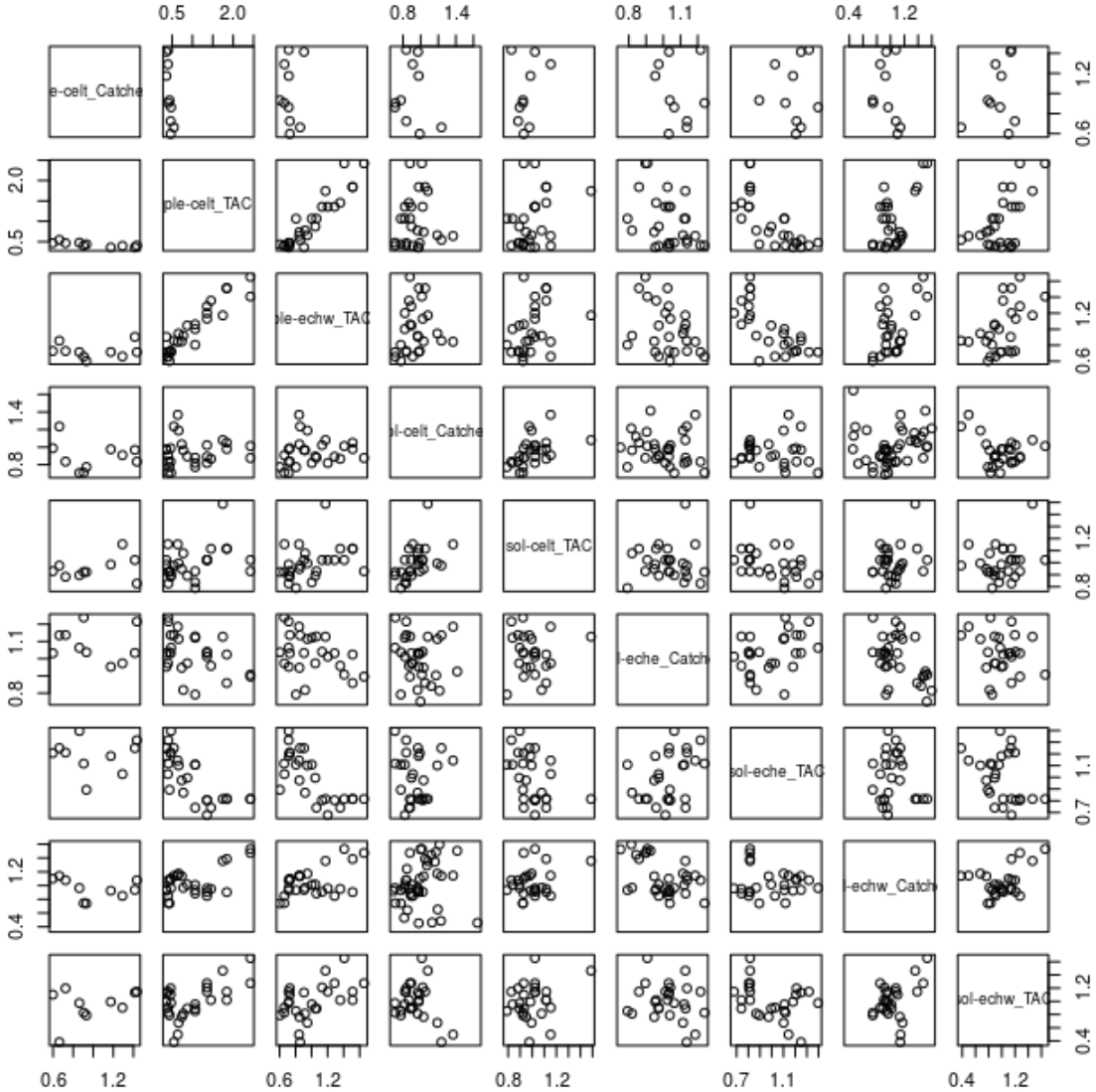

Figure 10: Pairwise plot of normalised catches and TAC (where available) for all species.

We get the data for the correlation plot. Note that catches from Eastern and Western Channel plaice are not included in the plot due to uncertainty over discards levels.

```
# Remove NAs
tacdc <- tac[!is.na(tac$dcpvalue), c("stock1","var1","meas1","stock2","var2","meas2","dcvalue","dcpvalu
tacdcv <- acast(tacdc, stock1 + var1 + meas1 ~ stock2 + var2 + meas2,
    value.var = "dcvalue")
tacdcp <- acast(tacdc, stock1 + var1 + meas1 ~ stock2 + var2 + meas2,
    value.var = "dcpvalue")
```

Many catches and TACs from a range of stocks are seemingly related (Figure 11). All of the TACs have significant relationships with the catches of the associated species, i.e. the TACs of Celtic Sea plaice and sole, Eastern Channel sole and Western Channel sole are all related to the their respective catches (although Eastern Channel sole has a relative low distance correlation score of 0.44). Additionally, there appear to be relationships between the catches and TACs of several stocks. For example, catches of Sole in the Western Channel (sol-echw) are related to catches of Celtic sole and Eastern Channel sole as well as the TACs of Celtic Sea plaice, Western Channel plaice. Similarly, the TAC of Sole in the Western

Channel is related to catches of Celtic sole and the TACs of Celtic Sea plaice, Western Channel plaice and Eastern Channel sole. The direction and shape of these relationships (e.g. inverse) is not apparent from the distance correlation score, only by inspecting the pairwise plot (Figure 10). The relationship between the TACs does not appear to be as simple them all decreasing or increasing in time i.e. the correlation scores are being biased through obvious trends in the timeseries (Figure 9). This demonstrates that the results from this kind of analysis can be hard to interpret.

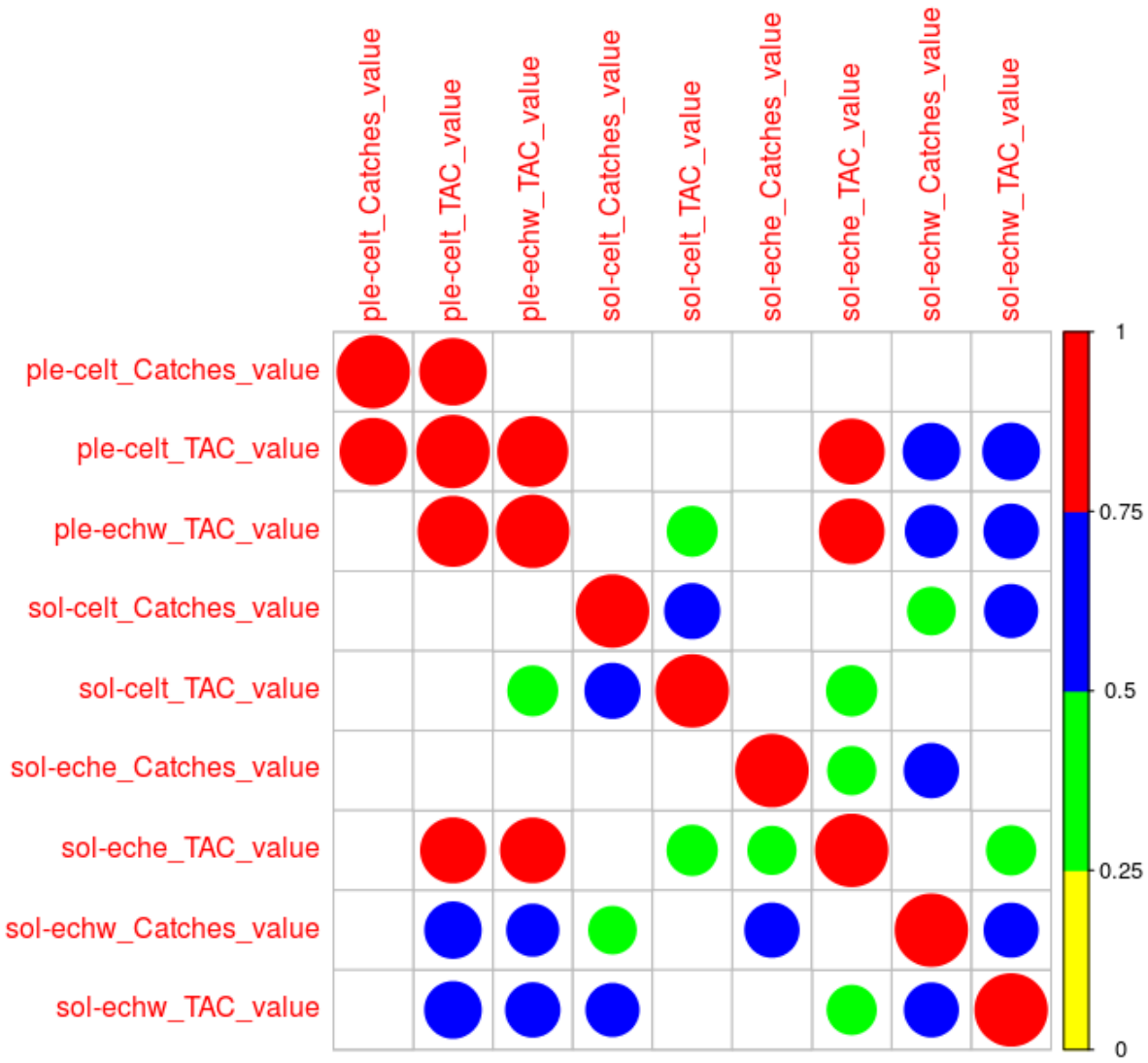

Figure 11: Distance correlation matrix for catches and TACs for all species. Only significant relationships (p <= 0.05) are plotted.

5.6 Recruitment

Here we look at how the estimated recruitment time series from each species are related.

```
rec <- dc[!(dc$stock1 %in% c("Oil")) & !(dc$stock2 %in% c("Oil")) &
          (dc$var1 %in% c("Recruitment")) & (dc$var2 %in% c("Recruitment")) &
          (dc$meas1 %in% c("value")) & (dc$meas2 %in% c("value")), ]
```

```
# Time series of these
rec_plot <- dat3[!(dat3$Stock %in% c("Oil")) & dat3$variable %in% c("Recruitment") &
    dat3$measure %in% c("value"),]
# Pairwise data
rec_pair <- dcast(rec_plot[,c(1,3,5)], Year ~ Stock)
```

The times series of recruitment shows a great deal of variability (Figure 12).

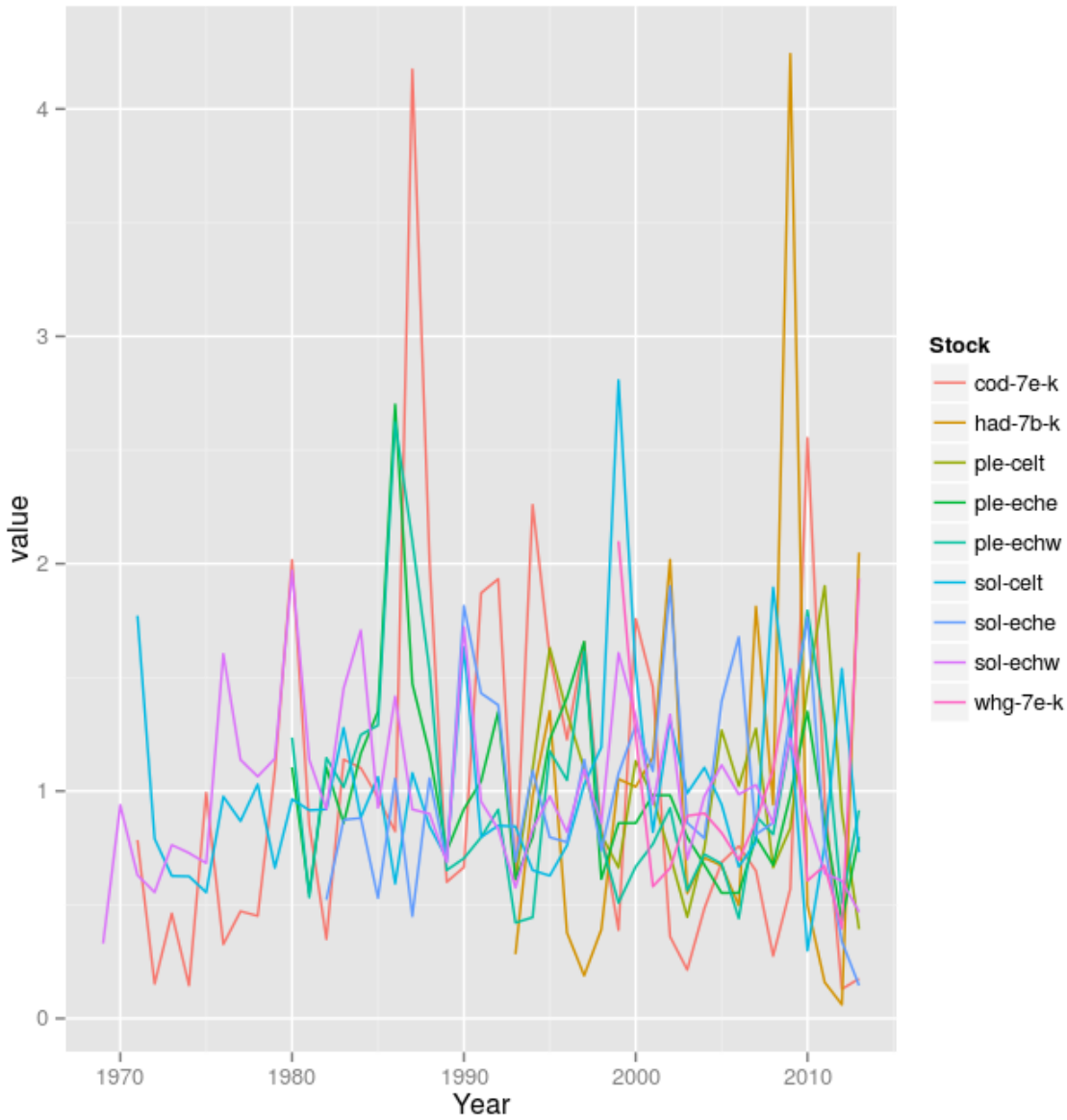

Figure 12: Time series of catches and TAC (if available) for all species.

A pairwise plot of recruitment can be seen in Figure 13.

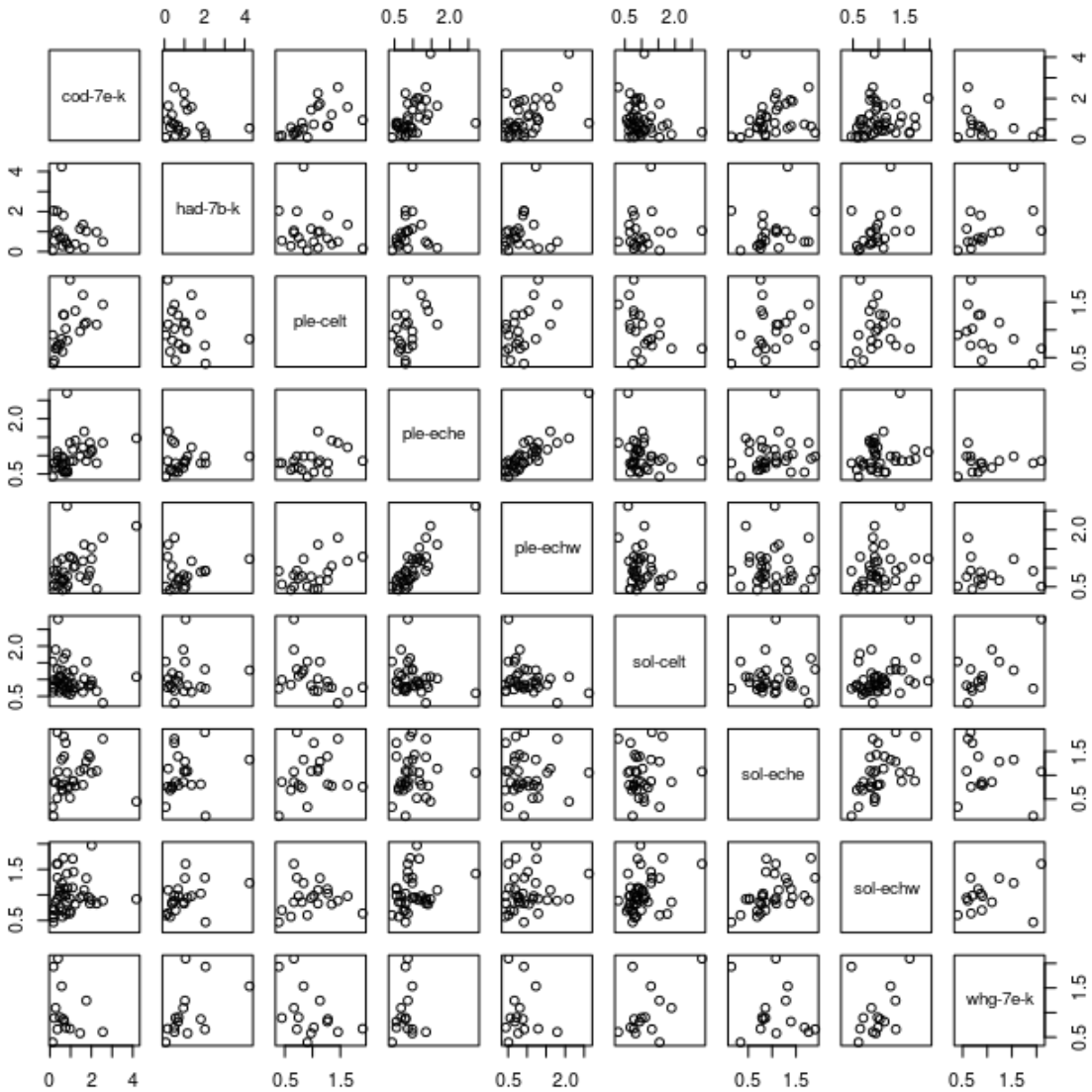

Figure 13: Pairwise plot of normalised recruitment data for all species.

```
recdcv <- acast(rec, stock1 + var1 + meas1 ~ stock2 + var2 + meas2,
    value.var = "dcvalue")
recdcp <- acast(rec, stock1 + var1 + meas1 ~ stock2 + var2 + meas2,
    value.var = "dcpvalue")
# remove rows with NA
recdcv <- recdcv[!(apply(recdcp,1,function(x)all(is.na(x)))) ,]
recdcp <- recdcp[!(apply(recdcp,1,function(x)all(is.na(x)))),]
recdcv <- recdcv[,!(apply(recdcp,2,function(x)all(is.na(x))))]
recdcp <- recdcp[,!(apply(recdcp,2,function(x)all(is.na(x))))]
```

The distance correlation matrix suggests that recruitment between cod in 7e-k, Celtic Sea plaice and Eastern and Western channel plaice are possibly related. Celtic Sea place and sole are also possibly related as are sole in the Eastern and Western Channels (Figure 14).

The recruitment estimates are model outputs rather than 'real' data so any results must be treated with caution. However, these relationships (between species, and between areas) suggest that some environmental drivers may be operating.

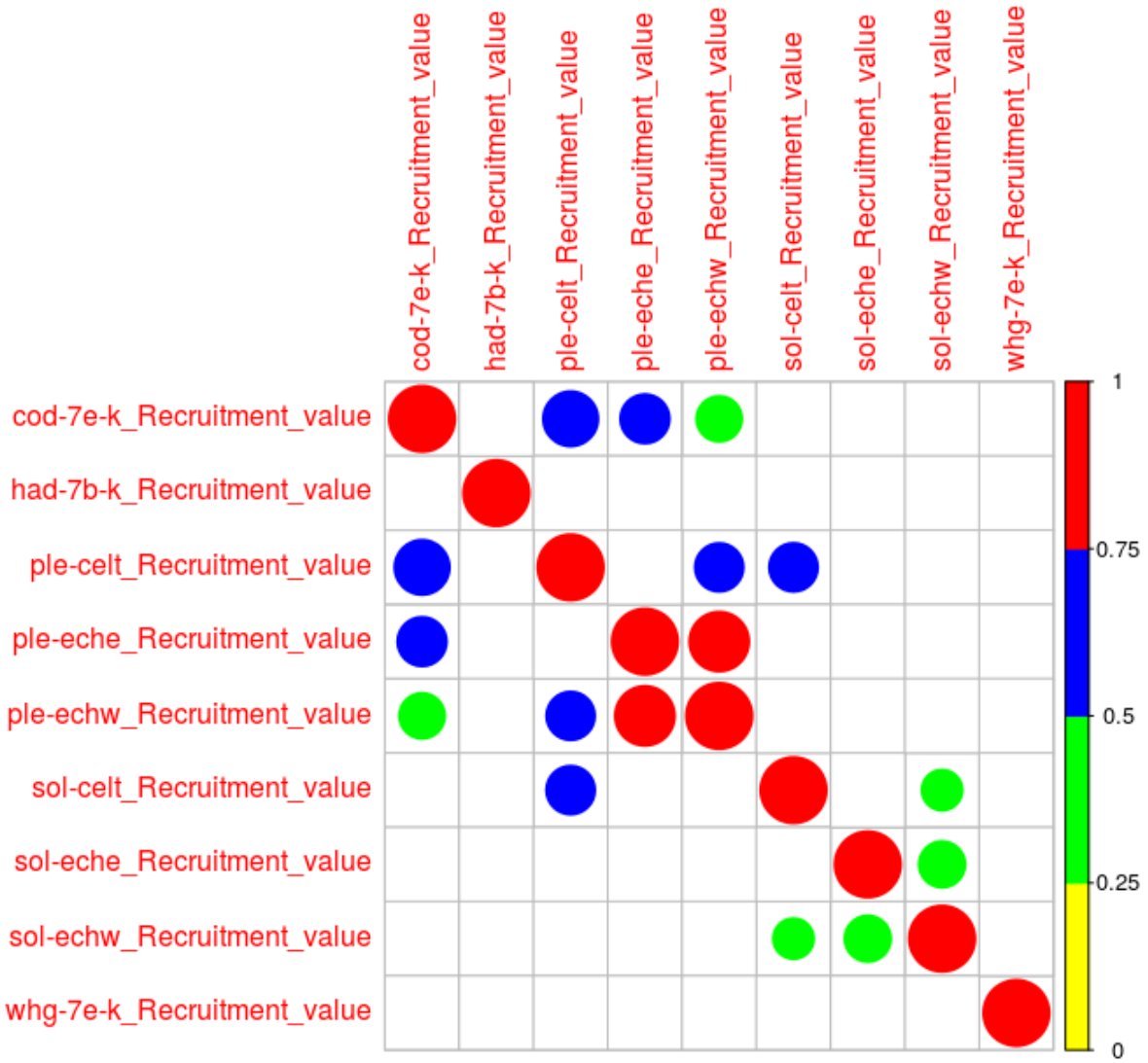

Figure 14: Distance correlation matrix for catches and TACs for all species. Only significant relationships (p <= 0.05) are plotted.

6 Conclusion

Given that the development and implementation of fisheries management plans can be expensive and time consuming, it is essential to be able to determine if a plan has been effective in acheiving its objectives. When the objectives of a management plan have been achieved (for example F, has been reduced to below some threshold level) it is also important to determine if it was as a direct result of the plan (for example, TAC restricting fishing mortality) or because of an external factor (for example, fuel price rises causing a reduction in fishing effort). These issues can become more complicated in mixed fisheries were multiple gear types catch multiple stocks.

One approach of doing this is to look at the relationships between a range of biological, economic and management variables from a selection of stocks and fleets in the area. Distance correlation is more useful than standard correlation for detecting non-linear associations between variables, particularly in terms of avoiding both Type I and Type II errors. We expect many relationships in fisheries to be non-linear

(for example, those between fishing effort and fishing mortality) and so distance correlation should be preferred to correlation for investigating these relationships.

In this technical report we have investigated how distance correlation can be used to investigate the strength of association between time series of different fisheries measures including estimates of biological productivity (recruitment), economic activity (catches) and management controls (TAC).

Distance correlation does not indicate the direction of the relationship, e.g. the values are from 0 to 1, whereas correlation values range from -1 to 1. Additionally, it must always be remembered that association does not imply causation. Despite this, the method shows a great deal of promise for investigating the impact of management plans and the relationships between measures and is a clear improvement over the use of standard correlations.

Any measure of association will require the time series to be of a minimum length and associations become easier to detect and confidence in them increases as time series get longer. Consequently, these methods can only detect impacts when sufficient data has been collected. This means that it will not be possible to detect the impact of a management measure with any degree of confidence until sufficient time has passed. As such, methods such as distance correlation may be of limited use when evaluating the impacts of recent management plans. However, by analysing historical data it may be possible to identify where and when the impact of a managment plan can be detected, thereby allowing us to learn from previous mistakes and successes.

Further analyses of the sole in Western Channel case study will be possible by linking economic and landings data through transversal variables. In particular, it will be interesting to investigate the associations between effort, variables costs and fishing mortality of the larger vessels, the reduction of which has been suggested as a key factor in the decrease of fishing mortality on sole.

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Abstract

The development and implementation of fisheries management plans can be expensive and time consuming. It is therefore essential to be able to determine if a plan has been effective in achieving its objectives. When the objectives of a management plan have been achieved (for example F, has been reduced to below some threshold level) it is important to determine if it was as a direct result of elements of the plan (for example, TAC restricting fishing mortality) or because of an external factor that was not included
or considered by the plan (for example, fuel price rises causing a reduction in fishing effort). In the former case, we want to be able to understand which aspects of a management plan were effective so they can be considered in the design for future plans. In the latter case, there is the possibility of falsely attributing success to aspects of a plan that had no impact, thereby needlessly including them in the design of future plans. These issues can become more complicated in mixed fisheries where multiple gear types catch multiple stocks because interactions between the different biological and economic elements are not straightforward.
To allow the evaluation of fisheries management plans it is necessary to develop and test biological and economic indicators. In this study we investigate potential indicators for evaluating the impact of management measures on the dynamics of fisheries and stocks subject to management plans. One approach of doing this is to look at the relationships between a range of biological, economic and management variables from a selection of stocks and fleets in the area. We expect many relationships in fisheries to be non-linear (for example, those between fishing effort and fishing mortality). Distance correlation is more useful than standard correlation for detecting non-linear associations between variables, particularly in terms of avoiding both Type I and Type II errors and so distance correlation should be preferred to standard correlation for investigating these relationships.
We go on to apply to these methods using sole in the Western Channel mixed fishery as a case study. Further analyses will be possible by linking economic and landings data through transversal variables. For example, it will be interesting to investigate the associations between effort, variables costs and fishing mortality of the larger vessels, the reduction of which has been suggested as a key factor in the decrease of fishing mortality on sole.

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