



Which design elements of individual quota fisheries help to achieve management objectives?

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Abstract

Individual quota (IQ) management systems in commercial marine fisheries are highly diverse, differing in the security, durability and exclusivity of the harvesting privilege and the transferability of quota units. This diversity in the degree of harvest rights may influence the effectiveness of IQ fisheries to meet management objectives. We conducted a global meta-analysis of 167 stocks managed under IQs to test whether the strength of harvest rights impacts the conservation status of stocks in terms of catch, exploitation rate and biomass relative to management targets. We used non-parametric methods to assess non-linear relationships and linear regression models to explicitly consider interactions among predictors. Most IQ fisheries consistently met fleet-wide quota limits (94% of stocks had recent catches below or within 10% of quotas), but only 2/3 of IQ fisheries adhered to sustainable management targets for biomass and exploitation rate (68% of stocks had exploitation rates below or within 10% of targets and 63% of stocks had biomass above or within 10% of biomass targets). Strikingly, when exclusivity of the harvesting privilege was low, exploitation rates depended on whether IQ implementation was industry-driven (exploitation below targets) or government-mandated (exploitation above targets). At high levels of exclusivity, exploitation rates converged to just below management targets. Transferability of quota units was associated with stock biomass closer to and slightly above target levels than stocks with non-transferable quota. However, regional differences had the strongest effect on biomass, suggesting that other management or biological attributes of regional fishery systems have greater influence on marine populations.

Keywords Fisheries management, ITQ, marine conservation, maximum sustainable yield, property rights, random forests

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Introduction

Fishery management systems are extraordinarily diverse in their design and operation, and variability in the strategies and tactics employed for managing fisheries is likely a major determinant of the biological status of marine populations around the world (Beddington *et al.* 2007; Worm *et al.* 2009). Most commercial marine fisheries in industrialized countries are regulated by an annual fleet-wide catch limit, or total allowable catch (TAC), which is typically set by applying a target exploitation rate to the estimated stock size consistent with management objectives of long-term sustainable yield. A major distinction of quota systems lies in whether individuals within the fleet compete for that TAC in a 'race to fish' or whether quota is allocated to entities: fishermen, vessels, companies or cooperatives. Individual quota (IQ) management systems, in which specific fractions of a total catch limit are allocated among entities, have been used in commercial marine fisheries around the world for decades. They have been promoted by some (Grafton 1996; Arnason 2005; Bonzon *et al.* 2013) or criticized (Copes 1986; Bromley 2005, 2009) and cautiously questioned or supported by others (McCay 1995; Fujita *et al.* 1998; Squires *et al.* 1998) for their perceived effects on economic efficiency, crew safety and year-round fresh product availability. More recently, IQs (commonly

termed 'catch shares') have received increased attention for their perceived ecological benefits for target species (Branch 2009; Chu 2009), potential reduction in the frequency of stock collapse (Costello *et al.* 2008), potential for making fisheries more predictable (Essington 2010; Essington *et al.* 2012) and their potential to better meet management targets compared to management systems employing other means of controlling catches (Melnychuk *et al.* 2012). Individual quotas are generally assumed to foster resource stewardship among fishermen by aligning individual incentives with conservation objectives (Hilborn *et al.* 2005; Grafton *et al.* 2006).

The individual allocation of quota is considered a harvesting privilege or secure access privilege, and parallels with property rights have often been drawn (Arnason 2005). Like other aspects of fishery management systems, however, IQ programmes vary widely in how they were established and how they currently function (McCay *et al.* 1995; Young 1995; Sanchirico *et al.* 2006; Anderson and Holiday 2007; Bonzon *et al.* 2013; Grainger and Costello 2014). In particular, IQ systems may differ in their degree of harvest rights as represented by the security, durability, exclusivity and transferability of the access privilege (Arnason 2005; Scott 2008). In turn, the strength of harvest rights may affect the extent to which IQs provide incentives that promote more

sustainable fishing practices. If an individual or entity holding quota shares cannot be certain of their share of the future benefits from stock rebuilding, they may be less likely to support reduced harvest in the present. Other attributes besides harvest-right elements may also affect the performance of IQ systems, including the number of years under IQs and how they were first implemented. A few programmes have operated for nearly 40 years while most began more recently. Some IQ programmes were primarily mandated by governments, for example several in New Zealand, Australia, Europe and South Africa, while others were largely driven by industry, for example many in Canada and the United States. The degree of resource stewardship and therefore the impact on population status are likely affected by these important details of IQ systems.

The conservation status of marine populations is often expressed with explicit reference to management targets based on objectives of sustainable production. The TAC is a fleet-wide limit set to control the level of harvest. Target reference points for stock exploitation rates (the fraction of the stock caught) and stock biomass are estimated through stock assessments and provide a benchmark to compare with estimates of current exploitation rates and biomass (Mace 1994). These target reference points are typically proxies for maximum sustainable yield (MSY), that is, values of stock biomass and exploitation rate expected to produce the greatest long-term catch. Owing to a variety of environmental, social, economic and management factors, these targets are rarely met in all years. Biomass in particular may be sensitive to ocean productivity changes over time and among regions (Vert-pre *et al.* 2013; Szuwalski *et al.* 2014), making it difficult to respond with various management measures in a timely manner to consistently achieve targets. For some stocks, the TAC and/or exploitation targets are consistently exceeded and biomass is below targets; other stocks are exploited at more conservative levels, and some show greater interannual variability than others. These variables are considered performance indicators of stock status and of how closely management objectives are satisfied (Worm *et al.* 2009; Melnychuk *et al.* 2012; Ricard *et al.* 2012).

Previously, we compared commercial marine fisheries managed under IQs with those managed only by fleet-wide catch or effort controls to assess whether IQs improved the ability to meet

management targets (Melnychuk *et al.* 2012) and to quantify the changes in population status and fishery production when IQs are implemented (Essington *et al.* 2012). We extend this previous work to consider only IQ fisheries and evaluate which particular attributes of these systems allow them to better meet management targets. We present a meta-analysis of 167 fish and invertebrate stocks from around the world managed under IQ systems to test the hypothesis that IQs with stronger harvest rights lead to improved conservation status of fish stocks with respect to management targets. We aim to identify specific characteristics of IQs that have relatively strong influence on conservation-related outcomes for marine populations.

Methods

We quantified the influence of particular attributes of IQ management systems on the conservation status of marine populations. Indicators of conservation status were based on time-series data drawn from stock assessments and were treated as (dependent) response variables. Data describing attributes of IQ systems, including harvest-right elements, were compiled by interviewing fisheries managers and scientists familiar with particular stocks and were treated as (independent) predictor variables. We applied two analytic approaches to assess which attributes were most important: random forests and linear mixed-effects models. Random forests are a nonparametric method that provides a straightforward ranking of the importance of predictors and allows for nonlinear relationships between response variables and predictors. Linear mixed-effects models allow for explicit consideration of interactions between predictors and provide a straightforward method for testing hypotheses of how predictors affect response variables. These approaches differ from time-series analysis or standard econometric analysis of 'panel data', in that we only consider average performance and variability in performance over a recent 5-year window rather than modelling temporal changes explicitly.

Data

We compiled IQ attribute data for as many stocks as possible that were managed under IQs and had data available for at least one indicator of conservation status. We included stocks from Canada, New Zealand, Australia, Iceland, Argentina, South

Africa and USA. Consistent with a previous study (Melnychuk *et al.* 2012), we used a 'snapshot' focal period from 2000 to 2004, representing a recent 5-year period for which data were available for most stocks.

Conservation status indicators explicitly accounted for management targets, involving ratios of total catch to total quota (catch/TAC), current exploitation rate to target exploitation rate (F/F_{target} or U/U_{target}) and current biomass to target biomass (B/B_{target}). Time-series estimates of exploitation rate (F) and biomass (B) were originally drawn from stock assessments and compiled in the publicly available RAM Legacy Stock Assessment Database (Ricard *et al.* 2012). Any explicitly stated management targets were assumed as target reference points. If none were explicit, biological reference points based on MSY, also compiled in the RAM Legacy Database, were considered as targets. If no target reference points were presented in stock assessments, MSY-based estimates from a Schaefer (1954) surplus production model fit to total catch and biomass time series were assumed as targets (Worm *et al.* 2009; Melnychuk *et al.* 2012). Time series of total catch

and TAC were collected, ensuring they represented the same quantities in terms of fishing areas, sectors, gear types, inclusion or exclusion of discards and inclusion or exclusion of recreational catches. Occasionally, some stocks were pooled together for catch/TAC data, dependent on how data were reported (Table S1). For each of the three types of ratios (which were treated in log space), two metrics were considered for each stock: the arithmetic mean and standard deviation around the mean of the \ln -ratios from 2000 to 2004. The semideviation (Porter 1974), a measure of asymmetric risk around a target value, was also calculated as a third metric, but results were consistent with those observed for the mean and standard deviation so results for semideviations are reported only in the Supporting Information.

As predictor variables, we considered four aspects of harvest rights of IQ systems that have been hypothesized to affect incentives for resource stewardship (i–iv; Table 1), as well as two additional attributes of IQs that may either directly impact the conservation status of stocks or mediate the effect of harvest-right elements on conservation status (v–vi):

Table 1 Individual quota (IQ) predictor variables (i.e. independent variables) and other covariates accounted for in our analyses of 172 IQ fisheries worldwide. All predictor variables were determined at the stock level for the 2000–2004 period.

Predictor variable	Description	Levels	Mean and range
Security/durability of IQs	Categorical. In practice, are IQs considered a permanent right that cannot be revoked ('yes'), or do they carry a limited duration or an unsecure tenure ('no')?	Yes 156, No 16	
Transferability of IQs among holders	Categorical. Can IQs be transferred among quota holders, either permanently or leased within a season?	Either/or 160, Neither 12	
Transferability of overages or underages	Categorical. Can catch overages or catch underages (relative to individual quota) be transferred to the following year?	Either/or 122, Neither 50	
Exclusivity of IQs	Numerical. The proportion of the total catch that is caught under programmes with individual allocations		0.89; 0.29–1.00
Industry involvement in IQ implementation	Categorical. Was the IQ programme primarily mandated by government, or did industry play a large role in driving its establishment?	Gov. 104, Ind. 68	
Years since IQs implemented	Numerical. The number of years since IQ programme was first established (first sector to implement, in cases of multiple implementations)		10.3; 0–26
Total catch	Numerical, natural log. Includes recreational catches and discards if data are available		7.85, 3.98–14.46
Year of fishery development	Numerical. The year in which total landings first reached 25% of the historic maximum annual landings in the entire time series		1968, 1911–2002
Age at first maturity	Numerical. The average age at reproductive maturity		4.7, 1.0–29.3

- (i) *Security/durability of the harvesting privilege.* In some IQ systems, quota shares are granted in perpetuity and the privilege is considered secure into the future by involved parties (even if not legally binding). In other systems, the allocation of individual quota is granted for a limited time or is considered an unsecure privilege that may be rescinded. We expect that secure and durable harvesting privileges will foster incentives for long-term stewardship and thus for maintaining populations at sustainable levels (Arnason 2005).
- (ii) *Transferability of shares among quota holders.* In some systems, quota shares can be sold (permanently) or leased (within a season), while in other systems transfers among holders are not permitted. In non-transferable systems for multispecies fisheries, individuals may reach their quota limit for one species, limiting their ability to fulfil individual quotas for other species (Squires *et al.* 1998; Sanchirico *et al.* 2006). Similarly, vessel or gear problems may leave an individual's quota unfished (Turris 2010). Further, if individuals do exceed their quota, they are not able to lease quota from others to cover that excess. We therefore expect non-transferable systems to be less consistent in meeting management objectives (i.e. have greater variability), and also on average to catch less than systems with ITQs.
- (iii) *Transferability of quota overages or underages to the following year.* In some systems, if an individual exceeds their quota limit, the excess is subtracted from their next year's quota (there may also be fines associated with overages). Or, if an individual does not fulfil their quota, a proportion of the unfulfilled quota is added to their next year's limit. Similar to (ii) above, these abilities can improve catch-to-quota balancing. We expect greater variability and a greater risk of exceeding management targets into undesirable states when overages or underages cannot be transferred.
- (iv) *Exclusivity of the IQ programme.* In some systems, the entire catch is under IQ management, but in others some portion of the catch is taken by competitive sectors or by recreational fisheries that are not under individual quota allocations. In non-exclusive systems, fishermen with IQs may be concerned about other sectors not having the same incentives for long-term stewardship (Grafton *et al.* 2006). Similar to (i), we expect that greater levels of exclusivity will result in populations being maintained at sustainable levels with lower risk of over-exploitation.
- (v) *Industry involvement in establishing the IQ system.* In some systems, industry played an important role in planning and implementing the programme, whereas in other systems it was primarily mandated by government, occasionally counter to the industry's wishes at the time. The history of the programme's implementation may affect compliance to management targets, in line with arguments about the benefits of stakeholder engagement into operational aspects of the fishery (Kaplan and McCay 2004). We expect that for IQ systems in which industry was heavily involved, the system may provide a better match to the social, economic and ecological components of the fishery system and thereby lead to catch and exploitation rates that are closer to management targets and at lower risk of exceeding these targets.
- (vi) *Number of years since IQs were first implemented (before 2000).* Some IQ systems in South Africa, Europe and Atlantic Canada were established in the mid-1970s, while others were adopted more recently. A greater duration of IQ management provides more time to adhere to management targets; catches and exploitation rates are expected to adjust rapidly, but it may take several years or decades for biomass to reach management targets if the population was overfished at the time of IQ implementation, especially for long-lived species.
- In addition to these IQ attributes, we accounted for three control factors in all analyses that may also affect conservation status (Table 1). The *ln* (total catch) was considered, as small fisheries may be more susceptible to fluctuations around management targets than larger fisheries (Melnychuk *et al.* 2012). Larger fisheries are also typically more valuable. The year of fishery development was determined for each stock, defined as the first year in which total landings reached 25% of the maximum historic landings in the full time series (Sethi *et al.* 2010). The average age at first maturity represents an important life history trait affecting a stock's potential to rebuild. Values for each species were obtained from FishBase (Froese and Pauly 2010), SeaLifeBase (Palomares and Pauly 2010) or stock assessments. In some analyses, we also accounted for the region

Table 2 Number of IQ stocks included in analyses of catch/TAC, exploitation rate-to-target exploitation rate (F/F_{target}) and biomass-to-target biomass (B/B_{target}) ratio variables. For each type of ratio, interannual means and standard deviations were calculated and used as response variables (i.e. dependent variables). Numbers are separated by region and by taxonomic/habitat association categories. Stock names are listed in Table S1 of the Supporting Information, and all values of response variables are given in a supplementary data file.

Category	Catch/TAC	F/F_{target}	B/B_{target}
Region			
USA – west coast/Alaska	4	4	4
Canada – west coast	30	14	16
Canada – east coast	25	5	7
USA – north-east/ mid-Atlantic coast	2	3	3
Europe	5	5	5
South Africa	5	4	5
South America	0	2	2
Australia	19	7	12
New Zealand	52	32	32
Taxonomic/habitat association			
Demersal fish	33	15	17
Bathymersal fish	15	16	18
Benthopelagic fish	41	23	27
Pelagic fish	14	8	10
Invertebrates	39	14	14
Total	142	76	86

and/or the taxonomic/habitat association of each stock (Table 2).

Several filters were applied to the data set prior to analyses. We focused on targeted stocks and excluded stocks in multispecies fisheries that were under IQ management but mainly caught as unwanted by-catch. We did not include stocks for which IQs were first implemented during or after the 2000–2004 snapshot period. If data for a response variable were not available for all five years, or if reliable reference points could not be obtained, the response variable was excluded. Finally, for catch/TAC and F/F_{target} analyses, we excluded stocks that were under a moratorium during 2000–2004 because they were not targeted. We still included these stocks for analyses of B/B_{target} , consistent with Melnychuk *et al.* (2012), because biomass in 2000–2004 partly reflects a management legacy prior to 2000 during which IQ attributes may have influenced the stock. After applying these filters, our data set of stocks managed under IQs consisted of 142 for catch/TAC

variables, 76 for F/F_{target} and 86 for B/B_{target} (Table 2; stocks are listed in Table S1).

Random forest analysis

Random forests (Breiman 2001a) are an ensemble of regression trees, a nonparametric recursive data-splitting method used to identify predictors with relatively strong influence on a numerical response variable. At a given node of a regression tree, values of the response variable and one predictor are split into two groups based on whichever predictor's split minimizes the response variable's sum of squared deviations. The procedure is repeated such that within a single tree, multiple predictors may split the response variable data set and thus have influence on the response variable. Although single regression trees are unstable in terms of the order of variable importance among predictors, random forests involve bootstrapping the data set (each component tree is constructed from one resampled data set) and only allowing a random subset of predictors to be included at any given node of a component tree, with the result being a more robust measure of variable importance across the aggregated set of trees (Breiman 2001b). Random forests have been used increasingly in ecology and fisheries research (Cutler *et al.* 2007; Gutierrez *et al.* 2011; Sethi *et al.* 2012; Melnychuk *et al.* 2013). They allow for nonlinear relationships between a predictor and response variable, make no parametric assumptions about the response variable, can handle missing values of predictors and are less susceptible to over-fitting compared with parametric methods such as generalized linear models because the number of predictors available for selection at any given node of a tree is limited to a specified number. Interactions between predictors are accounted for implicitly through the splitting procedure, but the ability to quantify or visualize interactions is limited.

For each of the six response variables, we conducted a random forest analysis using the 'randomForest' package (version 4.6–7; Liaw and Wiener 2002) in R (version 3.0.2; R Development Core Team 2014). The model for each analysis included all predictors listed in Table 1. Stocks were weighed equally. Forests of 10 000 trees were used, which were more than adequate for among-tree variance to stabilize. The cross-validation prediction accuracy represented by the mean

square error of model fit is sensitive to *mtry*, a tuning parameter that limits the number of predictors allowed for selection at any one node of a component regression tree. Larger values of *mtry* are often less susceptible to over-fitting large models and allow for higher-order interactions between predictors, while smaller values of *mtry* often have greater cross-validation prediction accuracy. The mean square error of model fit was plotted over a range of *mtry* values and suggested acceptable levels for *mtry* between 2 and 5. We used *mtry* = 5 because this permitted a higher order of possible interactions between predictors.

We show the influence of IQ attributes and other covariates on response variables using partial dependence plots. These plots show the nonlinear effect of a numerical predictor on a response variable after accounting for the average effects of other predictors in the model. We show overall relationships for each response variable, and in the Supporting Information, we further separate these relationships by geographical region. We express the effects of categorical predictors on response variables as the difference between marginal predictions of the response variable for each level of a categorical predictor. For each of the six random forest analyses, we show a measure of relative importance of predictors. The importance score is determined with cross-validation and reflects the loss of prediction accuracy associated with removing each predictor in turn (Liaw and Wiener 2002).

Linear mixed-effects model analysis

Mixed-effects models were used for three purposes: (i) to confirm results from the random forest analysis under the assumptions of linear relationships between response and predictor variables; (ii) to explicitly consider interactions between IQ predictors in their joint influence on response variables; and (iii) to compare candidate models containing different predictors in an information-theoretic framework. Response variables involved logarithms of ratios, and Gaussian models with an identity link were applied to these using the 'lme4' package (1.0–6; Bates *et al.* 2014) in R (version 2.15.2; R Development Core Team 2014). All models considered included taxonomic/habitat association as a random effect (Tables 2 and S1) and three control factors as fixed effects: $\ln(\text{total catch})$, year of fishery development and age at first

maturity (Table 1). First, to parallel the random forest analysis, a model including all six IQ attributes as main effects was applied to each of the six response variables to evaluate effect sizes of predictors on response variables. Second, multiple candidate models were applied to each response variable to evaluate the strength of interactions involving harvest-right elements and to evaluate regional influences in explaining variation in the response variables.

Candidate models were selected following a systematic approach to ensure that models represented a variety of hypotheses about which predictors – including interactions involving harvest-right elements – were influential. All models included the three control factors and the random effect, and the first model contained no other terms, that is, a null model. Models 2–7 each contained one of the six IQ attributes as well (Table 1). Model 9 included all of these attributes (hence, it is the model described in the previous paragraph). Model 8 included a categorical 'region' factor but no IQ attributes, and model 10 included 'region' and all six IQ attributes. Comparing these 10 models allowed us to identify whether regional factors, harvest-right elements or other IQ attributes (or all of these) best described the variation in response variables when considering only main effects. Eight additional models considered interactions between IQ attributes on top of the base terms. Interactions were explicitly considered because we hypothesized that influences of harvest-right elements on the biological response variables were likely to be mediated by: (i) the extent to which the fishing industry was involved in establishing the IQ system, because harvest rights may have little influence if industry was less involved; and (ii) the time elapsed since IQs were implemented, because influences may intensify over time, especially for biomass. These two IQ covariates, (i) industry involvement and (ii) years since IQ establishment, were each paired in turn with the four harvest-right elements of IQs to allow for eight two-way interactions. For each of the 18 total candidate models applied to the six response variables, we calculated Akaike's Information Criterion corrected for small sample size, AICc. Using the AICc, we derived Akaike model weights ranging from 0 to 1 (which sum to one across the 18 models), which represent the relative strengths of evidence for a particular model given the set of models.

Model assumptions and diagnostics

Several model checks and diagnostics were conducted to ensure that model assumptions were met and analyses were properly tuned to the data. Prior to mixed-effects model and random forest analyses, generalized variance inflation factors (GVIFs) were calculated to check for collinearity among predictor variables (Zuur *et al.* 2009). We had originally considered 'region' as an additional predictor, but this was highly confounded with other predictors on the basis of high GVIF scores so it was dropped from most analyses (it was kept in mixed-effects model 10). Under the full model of nine main effects (three base factors and six IQ attributes, used in both mixed-effects model and random forest analyses), all variance inflation factors were <3 , suggesting negligible multicollinearity (Zuur *et al.* 2009).

For random forest analyses, we conducted a sensitivity test, which incorporated a regional factor explicitly (with five levels) to allow for the possibility that response variables were influenced more strongly by region than by the six IQ predictors (see Supporting Information). There was little observable difference in partial dependence plots compared to the key run; even without the explicit region term, there was sufficient variation among regions in other predictors to explain regional differences in response variables.

For mixed-effects model analyses, we calculated pairwise correlations between fixed predictors, which were all <0.4 , suggesting limited concern for independence among predictors. We conducted graphical checks for assumptions of equal variance of response variables among groups of categorical predictors or throughout the range of numerical predictors. No notable deviations were observed. All 18 candidate models converged to each of the six response variables.

Results

The median catch/TAC ratio across 142 stocks was 0.91 (i.e. median of the back-transformed 5-year mean of \ln -ratios for each stock), and 86% of stocks had recent (2000–2004) average catches below their fleet-wide quota limits. If we allow a 10% exceedance of quota limits (i.e. a threshold of $1.1 \times \text{catch/TAC}$), 94% of stocks had recent catches below or within 10% of TACs, on average. Median F/F_{target} across 76 stocks was 0.74, and

64% of stocks had recent exploitation rates below their target exploitation rates, on average (or 68% of stocks were $<1.1 \times F/F_{\text{target}}$). Median B/B_{target} across 86 stocks (including those under moratoria) was 1.16, and 59% of stocks had recent biomass above their target biomass, on average (or 63% of stocks were $>0.9 \times B/B_{\text{target}}$). Effects of IQ attributes were observed for most of the catch/TAC, exploitation rate and biomass metrics considered.

Random forest analysis

Harvest-right elements and other IQ attributes had different effects on the six response variables, as evidenced by random forests that provide a ranking of predictor variable importance and allow us to visualize nonlinear relationships. Controlling for other variables, the ratio of total catch to TAC increased with increasing exclusivity between 30 and 50% exclusivity (i.e. 30–50% of the total catch was allocated under an IQ system), but had no effect at higher percentage exclusivity (Fig. 1). Exploitation rates also gradually increased with exclusivity, towards management targets. The interannual variability of catch/TAC and exploitation rate were both greatest when exclusivity was low (Fig. 1). Among the nine predictors, exclusivity was the most important in explaining variation in mean catch/TAC and in the interannual standard deviations of exploitation rate and biomass, as evidenced by relative importance scores. No effect of security and durability was observed on any of the six response variables (Fig. 2), although there were few fisheries whose IQs were considered to be insecure or of limited duration. Fisheries whose IQs were transferable among quota holders had lower mean B/B_{target} (Fig. 2), closer to management targets as revealed by inspection of category means. Counter to our expectations, the ability to transfer quota overages or underages to the following year did not affect any of the catch/TAC or F/F_{target} variables, but did exert a stronger effect for biomass. Individual quota systems in which quota overages or underages could be transferred to the following year were associated with mean B/B_{target} above management targets. In contrast, systems in which neither overages nor underages were transferable to the following year had lower B/B_{target} (Fig. 2), below biomass targets. When industry was heavily involved in establishing the IQ system, mean exploitation rates were lower (Fig. 2), further from management targets,

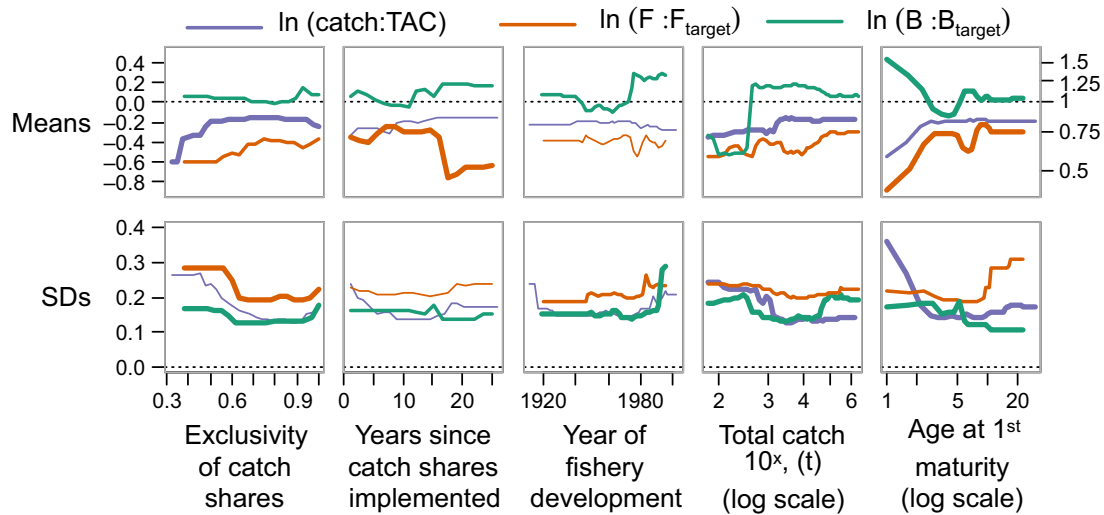


Figure 1 Partial dependence of catch to quota, exploitation rate to target exploitation rate and biomass to target biomass on five numerical predictors of IQ fisheries. Means and standard deviations of the log-ratios of three variables (catch/TAC, F/F_{target} and B/B_{target}) were calculated for each stock. These six response variables were analysed independently using random forests (10 000 trees, five predictors randomly sampled at each split). Line thickness is proportional to the relative importance score of the predictor for that response variable. Horizontal dotted lines at 0 represent general management objectives. Right-hand axis shows mean values on linear scale.

compared to cases where IQs were primarily government-mandated. Means and standard deviations of catch/TAC and B/B_{target} were relatively insensitive to the number of years since establishment of the IQ programme, but counter to our expectations, exploitation rates were considerably below target levels for fisheries in which IQs were established more than 15 years ago (Fig. 1).

Surprisingly, response variables were generally more sensitive to control factors than to IQ attributes. Fisheries that developed after the mid-1970s had greater mean B/B_{target} and also greater interannual variability in biomass compared with fisheries that developed earlier (Fig. 1). A strong marginal effect of total catch on biomass was observed. Fisheries with low annual catches of <250 t were associated with mean B/B_{target} that was considerably less and below target levels compared with larger fisheries (Fig. 1), although this is partly attributed to depleted stocks under moratoria generally having low total catches. Catch/TAC increased on average, was closer to management targets and was less variable as total catch increased. Fisheries for species that matured at ages 1–3 were associated with higher biomass and lower catch/TAC and exploitation rates, all further from management targets, compared with fisheries for species that matured later (Fig. 1). As might be

expected, the interannual variability in catch/TAC was higher for early-maturing species.

There were regional differences in the response variables, especially for biomass. New Zealand stocks were typically close to biomass, exploitation rate and catch/TAC targets (Figures S1–S3 in Supporting Information). Stocks from the east and west coasts of Canada had low exploitation rates relative to targets (Figure S2). For west coast stocks, this is the result of several stocks in a multispecies groundfish fishery not being primary targets (low F) and therefore having high biomass relative to target biomass (Figure S3). For east coast stocks, the data set for biomass indicators included stocks under moratoria (of which there are several in eastern Canada), so biomass relative to target biomass was on average low compared with other regions (Figure S3). Australian stocks had low catches relative to TACs, but exploitation rates and biomass were close to target levels compared with other regions, simply reflecting a different subset of stocks (there were more stocks with available catch/TAC data than with available F/F_{target} or B/B_{target} estimates, and the ones with only catch/TAC data tended to be less valuable so less heavily exploited). Differences in observed biomass ratios among regions could also reflect different productivity regimes during the focal period

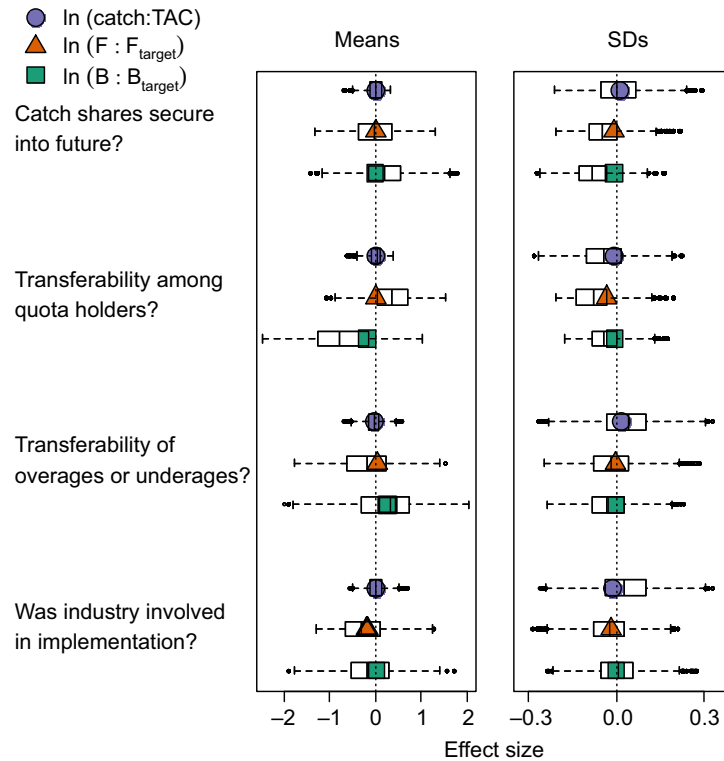


Figure 2 Effects of four categorical predictors of IQ fisheries on catch to quota, exploitation rate to target exploitation rate and biomass to target biomass. Means and standard deviations of the log-ratios of three variables (catch/TAC, F/F_{target} and B/B_{target}) were calculated for each stock. These six response variables were analysed independently using random forests. Effect sizes represent differences between predicted values of response variables for 'yes' and 'no' levels of the predictor (predicted values of 'yes' group minus predicted values of 'no' group). Coloured symbols show marginal effects of predictors on response variables (i.e. after accounting for other factors), with line thickness proportional to the predictor's relative importance score for that response variable. Overlaid boxplots summarize the distribution of 1000 calculated differences between randomly paired predicted values of response variables for 'yes' and 'no' levels of the predictor (i.e. they do not explicitly account for other factors).

(Vert-pre *et al.* 2013) or differences in enforcement. In contrast to mean responses, there were fewer differences between regions in the interannual variability of catch/TAC, F/F_{target} or B/B_{target} .

Mixed-effects model analysis

To check for consistency with the random forest analysis, we first considered the linear model with the same fixed effects that were included in the random forest analysis (model 9). This model with nine predictors explained between 24 and 58% of the variation for mean responses and 25–39% of the variation for interannual variability. Transferability of IQs among quota holders, that is, ITQs, was associated with mean B/B_{target} values that were lower (Fig. 3) and closer to target levels (based on visual inspections of category means)

compared with programmes with non-transferable quota. However, assuming model 10 that also includes region as a factor (discussed later), the transferability effect disappeared, so this response is confounded with region. The majority of stocks in our data set had ITQs; only a few stocks from the west coast of Canada, Argentina and the east coast of the United States had quota that could not be transferred. There was an unexpected effect of transferability of overages or underages from one year to the next on biomass. Mean biomass was higher (Fig. 3), above targets, when overages and/or underages were transferable, consistent with random forest results. This is not simply due to regional confounding, as model 10 also including region still yielded a significant effect for transferability of overages or underages. Involvement of industry in establishing IQ programmes was

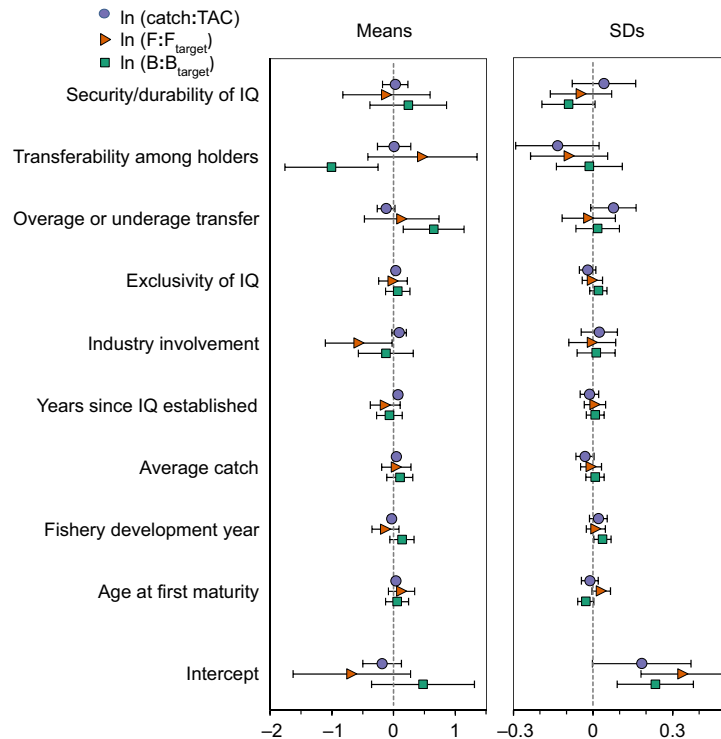


Figure 3 Estimated coefficients for effects of IQ and fishery predictors on catch to quota, exploitation rate to target, and biomass to target. Means and standard deviations of the log-ratios of three variables (catch/TAC, F/F_{target} and B/B_{target}) were calculated for each stock. These six response variables were analysed independently using linear mixed-effects models, treating taxonomic/habitat association as a random effect. Error bars show 95% CI around restricted maximum likelihood estimates of coefficients. The first four predictors are categorical, expressing the 'yes' group compared to the 'no' reference group.

associated with lower mean F/F_{target} compared with IQ programmes that were government-mandated (Fig. 3), consistent with random forest results. Note that assessment outputs were treated as data without error in our analyses, so 95% confidence intervals around the point estimates of F/F_{target} and B/B_{target} variables would be wider than shown if assessment uncertainties were propagated through our analyses.

In comparisons of 18 candidate models, standardized model weights indicate that mean and standard deviation of catch/TAC tended to be best explained by a single model, while for standard deviations of F/F_{target} and B/B_{target} , no single model was strongly supported (Fig. 4). Tables S1–S3 give full model comparison results for each response variable. Means of catch/TAC and F/F_{target} as well as the standard deviation of catch/TAC strongly favoured model 14, which allowed for an interaction between exclusivity and industry involvement. Mean B/B_{target} was best described simply by a

regional effect (model 8, Fig. 4), with west coast Canada and New Zealand having high B/B_{target} and Europe having low B/B_{target} , consistent with random forest results. Interannual variability of exploitation rates and biomass gave similar support to several models including the null model and models with a single IQ attribute, but little support to the inclusion of interactions (Fig. 4). No notable interactions were detected between the number of years since IQs were established and any of the harvest-right elements of IQs in their combined effect on any of the catch/TAC, F/F_{target} or B/B_{target} metrics (models 15–18, Fig. 4). Note that model 9, the model behind Fig. 3 used to compare with random forest results, had essentially no support for any of the six response variables, suggesting that interactions between IQ attributes and/or regional factors are important in explaining the variation in the data for these indicators.

The interaction model that was strongly supported by the data for three performance

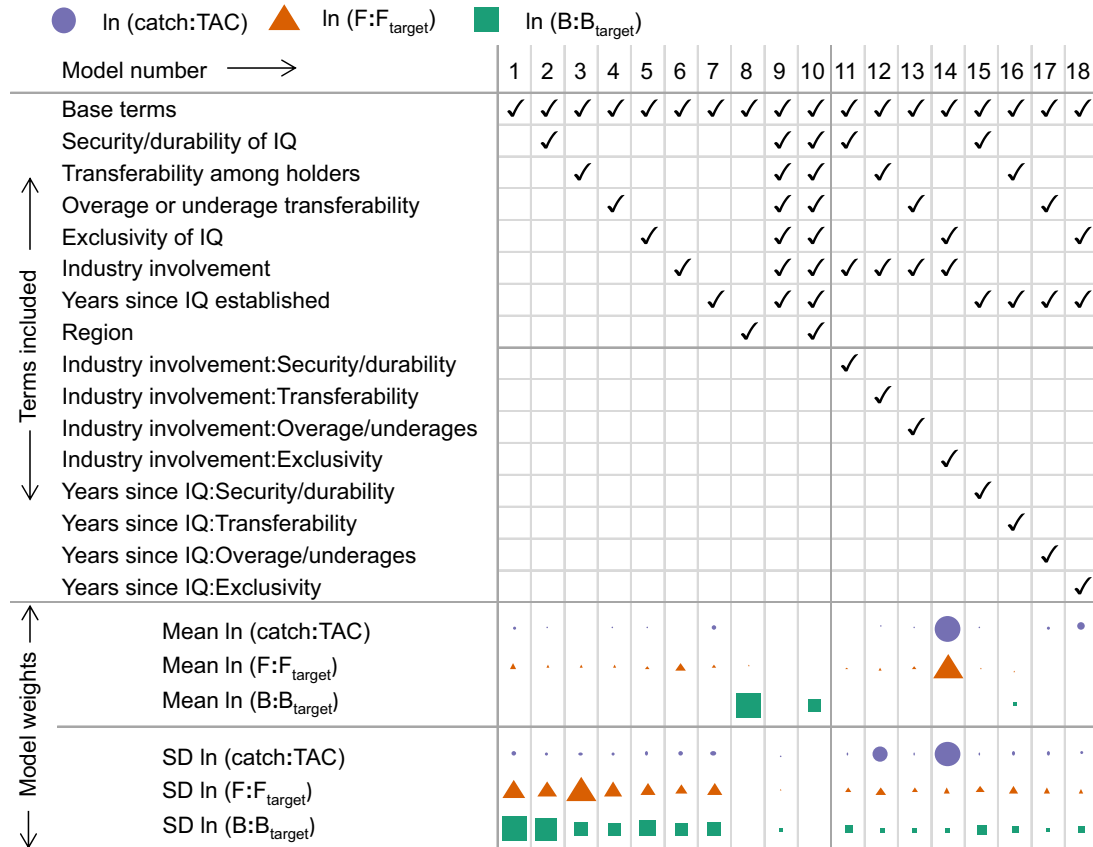


Figure 4 Comparison of candidate models for effects of IQ and fishery predictors on catch to quota, exploitation rate to target exploitation rate and biomass to target biomass variables. Two metrics (mean and standard deviation) of the log-ratios of catch/TAC, F/F_{target} and B/B_{target} were calculated for each stock. For each of the six response variables (rows at bottom), the AICc-preferred model is represented by the largest symbol; the area of symbols is proportional to the Akaike relative weight for the model, standardized to the AICc-preferred model. Base terms include $ln(\text{total catch})$, year of fishery development and age at first maturity as fixed effects as well as taxonomic/habitat association as a random effect. Models 1–10 involve only main effects, and models 11–18 also involve interactions.

indicators (model 14) reveals a noteworthy joint effect between exclusivity and industry involvement. Mean exploitation rates were higher, greater than management targets, when the harvesting right had low exclusivity and when the establishment of the IQ system was primarily government-mandated (Fig. 5). Mean exploitation rates were less than target levels when IQs had low exclusivity but more industry involvement in their establishment. At high levels of exclusivity, mean exploitation rates converged to just below target levels on average, irrespective of whether industry played a large role in establishing IQs. Despite having statistical support as the AICc-best model (Fig. 4), the interactions for mean catch/TAC and for standard deviation of catch/TAC were weaker (Fig. 5).

Discussion

A wide range of fishery management strategies and tactics are likely to impact the conservation status of marine populations. Management systems can be largely separated by whether they use input or output control approaches; within output controls such as TAC regulation systems, there is a further major distinction between individual allocation and competitive fisheries (Bromley 2009; Melnychuk *et al.* 2012). There is tremendous variability in management system characteristics at each of these levels, including those of IQ programmes. Despite including only a limited number of IQ attributes in our analyses, we found that our predictor variables could explain a

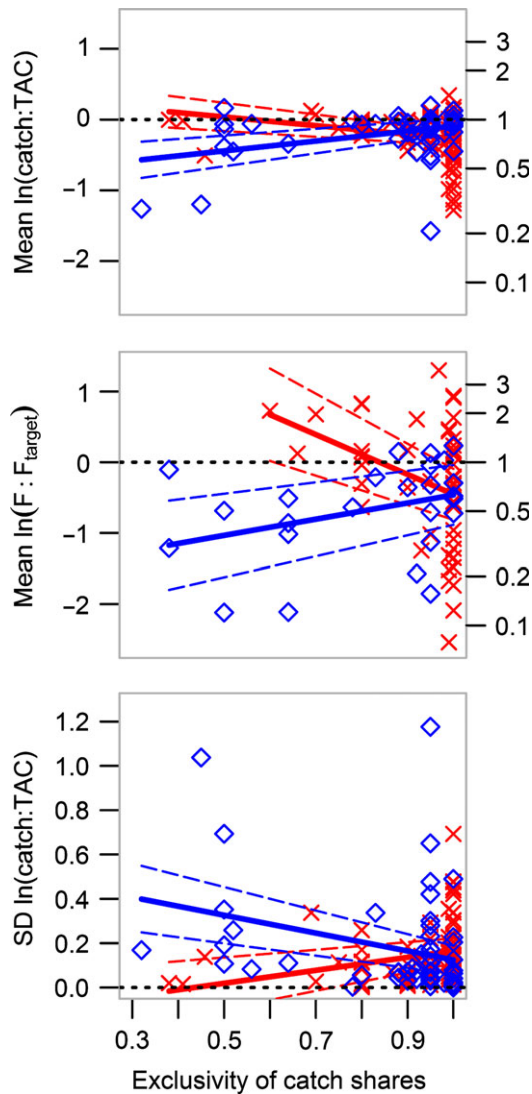


Figure 5 Effects of IQ exclusivity and level of industry involvement on mean catch/TAC, mean F/F_{target} and standard deviation of catch/TAC. Symbols show raw data, separated into groups of IQ implementation primarily government-mandated (\times) and IQ implementation jointly or mostly driven by industry (\diamond). Dashed lines show 95% confidence bands around predicted fits from a model allowing an interaction between IQ exclusivity and level of industry involvement (model 14). Horizontal dotted lines at 0 represent general management objectives. Right-hand axis shows mean values on linear scale.

reasonably high portion of the total variability in conservation-related performance indicators. This work follows up on previous work that compared IQ fisheries with non-IQ fisheries (Essington 2010; Essington *et al.* 2012; Melnychuk *et al.* 2012) by

quantifying which particular harvest-right elements and related attributes of IQs contribute to better meeting management targets.

Harvesting rights

It is believed (Arnason 2005) that IQs provide the greatest incentives for resource stewardship when they have strong access rights; prescriptions are widespread that the harvesting privilege should be secure, durable, exclusive and transferable (e.g. Scott 2008; Bonzon *et al.* 2013). Nearly 50 of the 167 stocks in our analyses (most from New Zealand, Australia and Atlantic Canada) met all of these criteria, but these stocks did not necessarily have the best overall conservation status. Likewise, many fisheries with incomplete harvesting rights consistently met their targets, so other factors also influence the ability to achieve management objectives. Overall, exclusivity was important not in isolation, but when it was mediated by involvement of the fishing industry in the establishment of the IQ system. When exclusivity was low, distinctions related to industry involvement were apparent, but at high exclusivity, these differences disappeared, suggesting that exclusive access to the resource may compensate for other factors to better meet management targets.

Transferability of quota

Transferability of a harvest right can be enacted among individuals or into the future. Transferability of quota among holders allows for more precise catch-to-quota matching because holders over their individual limits can lease quota from those with unused quota (Sanchirico *et al.* 2006; Branch and Hilborn 2008; Turriss 2010). When quota is not transferable, fishermen must try to exactly match their own quota allotment and face economic losses for catching less or face penalties for catching more than this amount. What we observed, however, was not an effect of transferability on catch/TAC ratios, but instead an effect on mean biomass of the stock: still above target levels, but closer to targets. This in part reflects regional confounding and a historical legacy of overfishing, since stocks under moratoria were included in the analysis of biomass metrics and pulled down the mean response across stocks. Several stocks from Atlantic Canada, in particular, have been under moratoria since the 1990s

despite being under ITQs. Similar to transferability among quota holders, the ability to transfer either a deficit or a surplus of individual quota from one year to the next is expected to aid in fishing efficiently by avoiding the necessity of exact catch-to-quota matching (Sanchirico *et al.* 2006). Counter to expectations, we observed effects of overage or underage transferability on increased biomass to above target levels, but little to no effect on catch/TAC or exploitation rate metrics. Unlike the case for transferability among quota holders, however, there was no regional confounding in this effect for biomass. If this variable is separated into transferability of overages and transferability of underages, most of the effect is attributed to the transferability of underages (*post hoc* results not shown). Causality may also be reversed in this case; permission to transfer underages may be more likely when biomass is above target levels, but if biomass is low, managers may be more cautious about allowing too high a quota in any one year because of transfers from the previous year. The association between high biomass relative to target levels and the ability to transfer quota underages is an avenue for further exploration.

Industry involvement

The involvement of the fishing industry in establishing IQs has rarely been considered in assessments of IQ programmes, but turned out to have an important influence on exploitation rates relative to targets. It seems reasonable that incentives to foster stewardship of the resource, which arise from the allocation of individual quotas, are likely to be stronger if industry played a large role in implementing the programme, rather than it being forced upon them by government. In some cases, industry associations are proactive in conducting or funding surveys and assessments, or participating in the management process (Hilborn *et al.* 2005; Grafton *et al.* 2006); in these cases, stock assessments, reference points and harvest control rules (upon which TACs are established) may be more widely accepted by industry. Industry associations may also be cautious about exploiting a stock for which they have a long-term harvesting right, and may argue to maintain lower exploitation rates than those based on MSY estimates (Pearse and Walters 1992). Fishers may even lobby for reduced TACs to maintain high prices (Branch 2009). Both of these possibilities would lead to

reduced F/F_{target} levels, but not necessarily to reduced catch/TAC ratios if the TACs are also lowered, as we observed.

Data analysis considerations

Fishery management systems are highly complex and also vary in other ways besides the factors we were able to consider in our analysis. IQ programmes typically have high levels of monitoring and enforcement, which likely also contribute to the degree of adherence to management targets (Squires *et al.* 1998; Parslow 2010). Other aspects of management systems such as spatial and seasonal closures, discard and by-catch limits, gear restrictions and reporting requirements also likely influence the performance indicators we considered (Squires *et al.* 1998; Sutinen 1999; Beddington *et al.* 2007; Worm *et al.* 2009). Similarly, aspects of fishing fleets such as gear type and duration of active season length may also affect these performance measures. Further, the IQ attributes we did consider as predictors were somewhat simplistic: four of these attributes were categorical, with simple yes/no levels. In reality, a wide range of values between these extremes with a diverse array of qualifications and caveats would more realistically capture the complexities of management systems. We were faced with comparing IQ programmes and management systems across diverse regions and taxonomic groups, so to maintain consistency, we reduced these complexities to simple categories. Given the sample sizes of 76–142 IQ fisheries in each analysis, we could not evaluate influences of all possible management predictors, so we focused on a few key elements of harvest rights hypothesized to affect the conservation-related indicator variables of catch to TAC, exploitation rate and biomass. This carries a risk of failing to identify important explanatory factors affecting the response variables, but focuses on possible effects arising from harvest-right elements. There is also not always a clear separation between independent (predictor) and dependent (response) variables, as the conservation status at some point in time may in turn affect some of the predictor variables such as total catch. This is a common feature in analyses of natural resource systems, but could affect the accuracy and precision of parameter estimates, so results should be interpreted in light of this caveat.

Conclusion

The effectiveness of fishery management systems in achieving objectives depends on a myriad of factors that may interact and may aid in meeting some objectives more easily than others. We focused on conservation-related objectives in this study, but there are also economic and social objectives in fisheries that may be influenced differently by the predictors that we considered, or most strongly influenced by a different set of management or fleet attributes altogether. In one recent study, Grainger and Costello (2014) found that New Zealand ITQ fisheries with greater security of harvest rights had lower dividend price ratios (ratio of quota lease price to sales price) and higher asset values than ITQ fisheries in Canada and the United States. Individual quotas are not a panacea for fisheries management (Fujita *et al.* 1998; Smith *et al.* 2009), but they have been observed to generate better adherence to TAC and exploitation rate targets than other frameworks to control catch (Melnychuk *et al.* 2012). Despite only looking at IQ fisheries in this study, we were surprised to find that 32% of stocks were being fished at exploitation rates $>1.1 \times F_{\text{target}}$ during the 2000–2004 period. Retrospective stock assessment errors may contribute to these cases of not meeting targets in any given year, but simply having IQ systems in place is clearly not sufficient to meet targets in many systems; the specific details of these systems including harvest rights matter (Scott 2008; Bonzon *et al.* 2013). Notably, it appears that stocks under IQ programmes established by government without a strong role of industry were at greater risk of recently undergoing overfishing, but that high levels of exclusivity to the resource access compensated for this by lowering exploitation rates towards targets. Counter to our expectations, it is also evident from the lack of any support for interactions between the four harvest-right elements and the number of years since IQ establishment that effects of these harvest rights do not strengthen over time. This suggests that any effects of harvest rights on population conservation status that may occur are just as likely to be observed soon after establishment as they are several years or decades later. At a time when IQ programmes are being widely implemented in fishery management systems around the world with varying degrees of harvest rights, these findings should be considered to improve the

chances of meeting management objectives under these programmes.

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Supporting Information

Additional Supporting Information may be found in the online version of this article:

Data S1. Values of response variables used in analyses.

Table S1. Stocks managed under IQs included in analyses.

Table S2. Model selection results for linear mixed-effects model analyses of catch to quota ratios: (a) mean $\ln(\text{catch}:\text{TAC})$; (b) standard deviation of $\ln(\text{catch}:\text{TAC})$; (c) semideviation of $\ln(\text{catch}:\text{TAC})$.

Table S3. Model selection results for linear mixed-effects model analyses of exploitation rate to target exploitation rate: (a) mean $\ln(F:F_{\text{target}})$; (b) standard deviation of $\ln(F:F_{\text{target}})$; (c) semideviation of $\ln(F:F_{\text{target}})$.

Table S4. Model selection results for linear mixed-effects model analyses of biomass to target biomass: (a) mean $\ln(B:B_{\text{target}})$; (b) standard deviation of $\ln(B:B_{\text{target}})$; (c) semideviation of $\ln(B:B_{\text{target}})$.

Figure S1. Partial dependence of three catch to quota metrics on five numerical stock-level predictors of IQ fisheries.

Figure S2. Partial dependence of three exploitation rate metrics on five numerical stock-level predictors of IQ fisheries.

Figure S3. Partial dependence of three biomass metrics on five numerical stock-level predictors of IQ fisheries.