Chromatin accessibility associated with aquaculture relevant traits in tilapia

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Abstract

The Nile tilapia (*Oreochromis niloticus*) accounts for ~9% of global freshwater finfish production however, extreme cold weather and decreasing freshwater resources has created the need to develop resilient strains. By determining the genetic bases of aquaculture relevant traits, we can genotype and breed desirable traits into farmed strains. We developed and optimised ATAC-seq from *O. niloticus* gill tissues to identify regulatory regions accounting for gene expression associated with gill adaptations. We find that SNPs from 27 tilapia species are enriched in noncoding regions, with 95% of accessible gene promoter regions being SNP-containing. Regulatory variants of TF binding sites are likely driving gene expression differences associated with tilapia gill adaptations, and differentially segregate in freshwater and euryhaline tilapia species. The generation of novel open chromatin data integrated with gene expression and genetic variants revealed candidate genes, genetic relationships, and loci associated with aquaculture relevant traits like salinity and osmotic stress acclimation.

Introduction

Tilapia cichlid fish of the genus *Oreochromis*, native to Africa and the Middle East, are farmed in over 120 countries/territories [1]. The Nile tilapia, *Oreochromis niloticus*, accounted for 9% of the 49 million tonnes of freshwater finfish produced globally in 2020, the third most of any species [1]. The exponential growth in tilapia aquaculture production is largely due to their suitability for aquaculture systems and unlike most other finfish species, tilapia can grow and reproduce in many culture systems. However, climate change is leading to extreme weather events, and decreasing freshwater resources. There is a pressing need to develop aquaculture systems based on strains resilient to saline waters and temperature changes. A way forward is to characterise the genetic bases responsible for such adaptive traits enabling selective breeding into farmed strains.

Such an approach involves resequencing populations to map and characterise variation, and identify signatures of selection in genomic regions associated with adaptive differences [2]. Previous population studies using whole genome resequencing of wild tilapia individuals (*O. niloticus*, *O. mossambicus*, and red tilapia) and commercial strains reported between 1.3 and 1.43 million single nucleotide polymorphisms (SNPs) [3,4], the majority of which are located within noncoding regions of the genome. Most SNPs under selection were found within those noncoding regions (45% intronic and 19% intergenic) and associated with several aquaculture relevant traits like growth, reproduction, and immunity [3,4]. Only 16 non-synonymous SNPs were identified in the three wild tilapia populations, suggesting selection on functional noncoding regions has played a prominent role during domestication/breeding [3].

We recently generated genome-wide sequencing data across 575 individuals of 27

tilapia species from across East Africa, to identify 69 million single nucleotide

polymorphisms (SNPs) in the *O. niloticus* genome assessing phylogenomic patterns

of recent and ancient hybridisation in tilapia (Ciezarek, A. *et al.*, bioRxiv TBC, 2023).

Whilst selection in noncoding regulatory regions, including transcription factor

binding sites (TFBSs) has been suggested as a key molecular mechanism

contributing to the evolutionary diversification of East African cichlids, including Nile

tilapia [5-7], no study has evaluated the *cis*-regulatory impact of noncoding variation

towards adaptive traits in a tilapia phylogeny.

Several studies have provided evidence on the role of *cis*-regulatory elements

(CREs) towards morphological diversity [8-10], including in mammals [11] and fish [12].

Whilst such studies identified CREs at particular loci, epigenetic sequencing

methods can capture chromatin accessibility and TF-binding at the genome-wide

level [13]. Only a handful of studies, all using DNA methylation, have applied

epigenetic approaches to study adaptive traits in tilapia [14]; this includes the

regulation of tilapia growth [15-17], sexual dimorphism [18], and sex determination [19,20].

ChiP-seq approaches have also been used to map active promoter elements

associated with Nile tilapia fin development [21]. However, such techniques are only

able to identify repressive or active marks at specific loci, and in the case of ChiP-

seq, direct interactions between a specific protein and DNA. In contrast, the assay

for transposase-accessible chromatin using sequencing (ATAC-seq) approach can

robustly identify genome-wide chromatin accessibility and TF-occupancy using very

few [22,23] or even single cells [24,25]. Despite the robustness of ATAC-Seq and its

potential to provide a better annotation of regulatory regions, and an accurate

identification of TF-occupancy including binding sites for regulators in Nile tilapia, no

such study has been performed to date on tilapia tissues and/or cells.

Here, we aim to identify genes and functional non-coding regions in Nile tilapia by

characterising the open chromatin and gene expression landscape of Nile tilapia gill

tissue to classify functional noncoding variation associated with environmental

tolerance. For this, we characterised the open chromatin landscape of Nile tilapia gill

tissue using ATAC-seq, and then identified accessible gene promoter regions with

TF footprints that could account for target gene expression in the gill. We integrate

this data with noncoding regulatory SNPs from a 27 species tilapia phylogeny

(Ciezarek, A. *et al.*, bioRxiv TBC, 2023), and identify candidate genes with regulatory

variation that could be associated with aquaculture-relevant traits, like salinity

tolerance.

Results

Accessible gene promoter regions in gill tissue are functionally associated with aquaculture relevant traits

To characterise functional noncoding regions based on chromatin accessibility, we performed high-depth ATAC-seq of gill tissue from three replicate male Nile tilapia individuals, identifying 301,293 open chromatin (accessible) reproducible peaks between replicates (see '*Materials and Methods*'), that could be associated to 25,092 (average of 12 accessible peaks per gene) out of 29,552 (85%) annotated Nile tilapia genes [26]. We first annotated (Supplementary Table S1) and tested the enrichment of accessible peaks in coding and noncoding regions, finding that peaks are mostly enriched (fold enrichment >2.1, adjusted *P*-value <0.05) in both sets of conserved noncoding elements (CNEs) (Fig. 1) that we annotated in the Nile tilapia (*O. niloticus* UMD_NMBU [26]) reference genome (see '*Materials and Methods*').

We focused on gene promoter regions, taken as up to 5 kb from the transcription start site (TSS) [7], as they harbour regulatory binding sites e.g., TFBSs that have functionally diverged [6,7], and can be associated with gene expression differences in Nile tilapia and East African cichlids [7]. Out of the 301,293 open chromatin (accessible) peaks, 127,602 accessible peaks (average size of 464 bp) were found within gene promoters of 20,248 genes in gill tissue, with missing genes being better associated to lymphoid tissues (see '*Supplementary Information*', Supplementary Fig. S1 – S2).

Accessible gene promoter regions could account for expression changes of genes associated with osmoregulation and salinity tolerance

To examine any correlation between gene transcription and accessible gene promoter regions, RNA-seq data was generated from the same gill tissue sample of the three replicates and gene expression measured using transcripts per million (TPM) (see '*Materials and Methods*'). Of the 29,552 Nile tilapia genes in the genome, we identified and calculated the expression (as TPM) of 20,717 (70%) genes. We found 96,784 (76%) accessible peaks could be associated to the expression of 14,842 genes.

We first tested whether these peaks are better correlated to their corresponding gene expression based on proximity to the transcription start site (TSS) (Fig. 2a). For this, accessible peaks are categorised into four intervals of either 500 bp (12,978 peaks), 1 kb (27,975 peaks), 2kb (48,108 peaks) or up to 5 kb (127,602 peaks) from the genes TSS. We found similar weak positive correlation (R = 0.13 to 0.14, Spearman $p < 2.2e-16$) for all four intervals (TSS peak up to 500 bp, 1 kb, 2 kb and 5 kb) (Fig. 2a) and thus, we focus on all (159,708) accessible gene promoter peaks (up to 5 kb from the TSS). A higher correlation might not be observed in our datasets as accessible regions are not always associated with gene activity and can instead, be associated with repressed or poised for activation genes [27-30].

Based on an approach devised previously [30], we explore the relationship of accessible peaks and gene expression by assessing genes with combinations of high accessibility (HA) or medium–low accessibility (MA), and either highly expressed (HE) or medium–low expression (ME) (see '*Materials and Methods*').

After categorising gene peaks and expression, we were left with a total of 27,536

(22% of 127,602) accessible peaks associated to the expression of 4,509 unique

genes. These could be placed into the four categories, with most genes (1,650) and

peaks (10,488) in the HA-HE category, and the remaining being either HA-ME (6,961

peaks and 1,081 unique genes), MA-HE (5,990 peaks and 1,770 unique genes), or

MA-ME (4,097 peaks and 1,164 unique genes). Whilst the HA-ME genes exhibit no

correlation (R = -0.021, Spearman p = 0.076), and the MA-HE genes exhibit

significant weak negative correlation (R = -0.034, Spearman p = 0.008), both the

MA-ME (R = 0.037, Spearman p = 0.019) and HA-HE genes (R = 0.031, Spearman

p = 0.0013) exhibit significant weak positive correlation (Fig. 2b). Among the 1,650

HA-HE genes, we identify genes associated with aquaculture-relevant traits,

including those enriched (FDR < 0.05) for the GO terms 'cellular process' e.g., *prlr1*

involved in tilapia salinity tolerance [31] and *clcn2* an osmoregulatory gene involved in

adaptation to saline-alkali challenge in tilapia [32], and 'cellular respiration' e.g., *cox4*

involved in aerobic metabolism changes under salinity challenge in tilapia gills [33]

(Supplementary Fig. S3).

Nile tilapia SNPs are enriched in noncoding regions

Since we previously found that discrete variation in regulatory regions disrupt

regulatory network interactions for adaptive trait genes in Nile tilapia [6,7], we tested

whether functional noncoding SNPs could be associated with the regulatory activity

of genes involved with aquaculture-relevant traits, like environmental tolerance.

Building upon our previous work of identifying 69 million (69,064,774) SNPs across

27 tilapia species (Fig. 3a, Supplementary Table S2) mapped to the Nile tilapia

genome (Ciezarek, A. *et al.*, bioRxiv TBC, 2023), we identified that these SNPs are

significantly enriched in noncoding than coding (exonic) regions (Fig. 3b). Compared

to exonic regions (fold enrichment of 0.9, adjusted *P*-value <0.05), the SNPs are

most enriched in either intronic or up to 5 kb gene promoter (fold enrichment of 1.1,

adjusted *P*-value <0.05) regions (Fig. 3b).

To characterise functional noncoding variation, we find that of the 5,470,066 SNPs in

Nile tilapia gene promoter regions, 1,083,195 (20%) SNPs overlapping 121,404 of

the 127,602 (95%) accessible peaks are significantly enriched (fold enrichment of

1.1, adjusted *P*-value <0.05) (Fig. 3c). Of the 20,248 accessible gene promoters,

20,101 (99%) have SNPs in accessible regions, representing 68% of all annotated

Nile tilapia genes [26]. Most SNPs are rare variants (Minor Allele Frequency, MAF <=

0.1) with 1% more rare variants found in noncoding regions that are accessible than

not (Supplementary Fig. S4, see '*Supplementary Information*'). Using the 127,602

accessible peaks in gene promoter regions, we find that the topmost (-log10 FDR <

0.05 of >=10) enriched GO biological processes of 20,248 accessible gene promoter

regions harbouring SNPs could be functionally relevant to aquaculture traits like, for

example, signalling, cell communication, and cellular response to stimulus (Fig. 3d,

Supplementary Fig. S5). In summary, nearly three-quarters of all Nile tilapia genes

have putative functional noncoding variation at gene promoter regions that could be

associated with the regulation of aquaculture traits relevant to gill function like, for

example, a response to stimulus.

Discrete variation in accessible TFBSs is likely driving gene expression

associated with tilapia gill adaptations

We hypothesised that genetic variation between Nile tilapia and the 26 other tilapia

species (Fig. 3a) could be used to identify functional noncoding variation based

associated with aquaculture traits that differ between the species. For example,

genetic variation in gene promoter TFBSs between Nile tilapia (a freshwater species)

and any euryhaline species e.g., *A. grahami, O. mossambicus* or *O. urolepis* with

exclusive homozygous or heterozygous alternate sites could indicate positive

selection acting on discrete mutations, that can be functional based on chromatin

accessibility in Nile tilapia gill tissue, and subsequently associated to target gene

expression of gill-specific traits relevant to aquaculture e.g., salinity tolerance. To

prioritise predicted TFBSs (see '*Materials and Methods*' and '*Supplementary*

Information'), we use the best described method for ranking predictions [34] by

overlapping predicted TFBSs with the number of reads (tag count, TC) in the

footprint, and then rank TFBSs using the bit-score of the motif match within ranked

tag counts. Based on a mean bit-score of 11.5 and mean tag count of 111.9, we

identify 6,195,938 TFBSs above the means (Fig. 4a). In gene promoter regions, we

identify 246,296 TF footprints with 2,491,107 non-redundant TFBSs (see '*Materials*

and Methods'). Based on a mean bit-score of 11 and mean tag count of 152.6, we

identify 398,995 (16%) TFBSs above the means in gene promoter regions.

Using TFBSs in accessible gene promoter regions, we identified a total of 3,398,768

transcription factor (TF) – target gene (TG) relationships in Nile tilapia. We then

identify discrete mutations in TFBSs to characterise conservation or divergence and

therefore, whether the 3,398,768 Nile tilapia TF-TG relationships could be present or

absent in the other 26 species. First, we map open-chromatin peaks, footprints,

TFBSs and SNPs to gene promoter regions on each Nile tilapia chromosome (Fig.

4b). In total, we identify 7,029,307 (11% of total 69,064,774) SNPs overlapping

accessible gene promoter regions, TF footprints, and TFBSs with all (2042) TF

motifs having at least one discrete mutation in 18,899 genes (64% of the 29,552 Nile

tilapia genes in the genome [26]). More than half (62% - 11,790) of the 18,899 genes

have SNPs in 'prioritised' TFBSs where the bit-score of motif match and tag count

are above the means of 11 and 152.6 respectively. Of the 18,899 genes, 1,562 (8%)

have high accessibility and high expression (HA-HE), which makes up the majority

(95%) of all 1,650 HA-HE genes. This indicates that discrete variation in accessible

gene promoter TFBSs could be a core factor driving high levels of gene expression

associated with environmental tolerances of the gill. Using both measures, we

narrowed this down to 1,168 genes (71% of all HE-HE genes or 6% of all genes with

a SNP in an accessible gene promoter TFBS) that are categorised as 1) having a

SNP in a 'prioritised TFBSs' where the bit-score of motif match and tag count are

above the mean of all gene promoter TFBSs; and 2) being a 'HA-HE gene' based on

peak-expression correlations. To further narrow down the 1,168 genes, we focus on

genes 3) with 'genetic variation' that exists between species exhibiting a gradient of

environmental tolerance e.g., freshwater versus saline water; and 4) that are

enriched for biological process GO terms that are associated with gill adaptations of

traits with aquaculture relevance e.g., response to stimulus (Fig. 3d, Supplementary

Fig. S5) or cellular process (Supplementary Fig. S3). We use these four described

criteria for identifying examples of candidate genes that are likely involved in gill

function associated with environmental tolerance in tilapia.

Discrete mutations at accessible regulatory sites of adaptive trait genes are

associated with environmental tolerance networks in tilapia species

Using the four described criteria (prioritised TFBSs, HA-HE gene, genetic variation

between diverse species, and aquaculture relevant GO terms) on the set of 1,168

genes, we first identified STAT1-*prlr1* (Fig. 5) as a candidate TF-TG relationship that

could be involved in gill adaptations associated with tilapia environmental tolerance.

The STAT1 TFBS is proximal (<400 bp) to the *prlr1* TSS (Fig. 5a-b) and with a

significant signal of activity (Fig. 5c), has a few standard deviations higher bit-score

of motif match (11.04 ± 2.61 SD) and tag count (152.6 ± 0.12 SD) than the means of

all predicted gene promoter TFBSs. Differences in the regulation of prolactin (PRL)

and its receptors (PRLRs) have been shown to underly variation in salinity tolerance

of tilapias [31], and are differentially expressed between *A. grahami* and the freshwater

species, *O. leucostictus* gill transcriptomes [35]. For this reason, genetic variation at

the TFBS for STAT1 could account for *prlr1* gene expression changes associated

with salinity response in different tilapia species. We identified a rare variant (LG7

position 18107947; MAF=0.03) at the third position in the predicted STAT1 TFBS

(Fig. 5b and Fig. 5d). The rare variant is homozygous alternate G/G (n=14) and

heterozygous alternate T/G (n=9) in the highly adapted extremophile species, *A.*

grahami, but homozygous reference T/T in Nile tilapia and the other 25 tilapia

species (Fig. 5d). STAT1 is a transcriptional activator that can be phosphorylated via

osmotic stress [36]; this suggests that STAT1 could be a key regulator of *prlr1* gene

expression in most tilapia species gills in response to osmotic stress however, the

loss of STAT1 regulation of *prlr1* could necessitate gill adaptations to extreme

alkaline and saline waters that are natural to *A. grahami* [37,38].

In another example, we identify variation in the gene promoter region of *cldnh* (also

referred to as *cldn3-like* and *cldn28a*), associated with expression differences in

stickleback ecotypes [39] and euryhaline tilapia [40] under salinity challenge, as well as

involved in permeability changes associated with salinity acclimation in freshwater

tilapia species too [41]. Specifically, we identify SREBF2-*cldnh* (Fig. 6) as another

candidate TF-TG relationship that could be involved in gill adaptations associated

with salinity acclimation, especially of freshwater species. The SREBF2 TFBS is

proximal (<330 bp) to the *cldnh* TSS (Fig. 6a-b) with a significant signal of activity

(Fig. 6c), and a few standard deviations higher bit-score of motif match (11.04 ± 0.4

SD) and tag count (152.6 ± 0.3 SD) than the means of all predicted gene promoter

TFBSs. We identified a rare variant (LG10 position 17991869; MAF=0.07) at the 4th

position in the predicted SREBF2 TFBS (Fig. 6b and Fig. 6d). We identify the rare

variant is mostly homozygous alternate G/G (n=19) and heterozygous alternate A/G

(n=14) in the freshwater species, *O. esculentus,* but homozygous reference A/A in

Nile tilapia, *O. esculentus* (n=4) and most individuals, except *O. "mtera"* , of the other

25 tilapia species (Fig. 6d). Despite being a freshwater species, *O. esculentus*

individuals with heterozygous and homozygous alternate genotypes were collected

from saline/alkaline water bodies, namely Hombolo Dam [42], Lake Malimbe [43], and

Lake Rukwa [44,45]. Such genetic variation at the SREBF2 TFBS could therefore

account for differential expression of the *cldnh* gene, which has been previously

shown to reorganise gill tight junctions in response to salinity acclimation of

euryhaline [40] and freshwater [41] tilapia. Discrete mutations in regulatory sites of

aquaculture relevant genes could therefore be driving gene regulatory evolution

associated with salinity acclimation of the gills.

Discussion

Most (~90%) tilapia aquaculture production is based on Nile tilapia [46] owing to its high growth and reproduction rate in several culture systems. However, with climate change leading to extreme weather and human competition decreasing freshwater resources, there is a crucial need to breed tilapia strains that are resilient to broad environmental conditions. One method to determine the genetic bases responsible for environmental traits e.g., salinity tolerance, involves firstly characterising genetic variation and signatures of selection associated with adaptive traits in resequenced populations [2] and then secondly, using epigenetic sequencing e.g., ATAC-Seq to annotate functional genomic regions and RNA sequencing to characterise whether these loci can drive gene expression change. Despite the impact of noncoding regulatory evolution towards the diversification of cichlids, including Nile tilapia [5-7] and breeding wild tilapia populations [3,4], no previous work has applied ATAC-Seq to accurately identify transcriptional regulators in tilapia tissues and/or cells, let alone classify functional noncoding variation associated with adaptive traits.

By performing high-depth ATAC-seq of Nile tilapia gill tissues, we identify 301,293 accessible (open chromatin) regions in three replicates that can be associated to 85% of all annotated Nile tilapia genes [26]. No previous work has carried out ATAC-seq in gill tissue however, we identify more peaks in our study compared to 11 other zebrafish tissues (66k-180k peaks) but fewer than the 436k merged non-redundant peaks across all tissues [47]. The identification of more single tissue peaks than zebrafish is possibly due to tissue-specific differences and sampling of more replicates. More than 40% (127,602) of the accessible regions can be found within

gene promoter regions of 20,248 genes, with genes without a reproducible peak

being better associated to functions of lymphoid tissues not sampled here.

We were able to associate 96,784 (76%) accessible gene promoter regions to the

expression of 14,842 genes. After determining no difference in weak positive

correlation of accessible peaks to gene expression based on proximity to the TSS,

we found that most genes (1,650 out of 4,509) could be categorised as highly

accessible and highly expressed (HA-HE) based on signals and counts above the

70th percentiles. The HA-HE genes are enriched for genes involved in salinity

acclimation however, the overall set exhibits weak positive correlation of accessibility

and gene expression. A higher correlation might not be observed in our datasets as

accessible regions are not always associated with gene activity and can instead, be

associated with repressed or poised for activation genes [27-30]. Like previous work in

C. elegans [27], this would need to confirmed using relevant (H3K27me3 and H3K4

methylation) ChiP-Seq marks.

Whilst our previous work focused on regulatory variation in a phylogeny of five cichlid

species, including Nile tilapia [6,7], no previous work has examined functional

noncoding variation in the tilapia phylogeny. Building upon our recent work of

identifying 69 million SNPs in the Nile tilapia genome based on resequencing

populations of 27 tilapia species (Ciezarek, A. *et al.*, bioRxiv TBC, 2023), we found

SNPs are enriched in noncoding regions and more specifically, gene promoter

regions. We identified that gene promoter regions with accessible SNPs are enriched

for processes associated with gill function e.g., response to stimulus, and therefore

conclude that much like the adaptive radiations of East African cichlids [6,7], discrete

variation in regulatory regions can also drive gene regulatory rewiring of tilapia

adaptive trait genes. This is supported by the fact that nearly all (99%) accessible

gene promoter regions have a SNP with most (90%) being a rare variant. Gene

promoter regions are enriched for TFBSs [7], as are accessible regions [47,48], and thus,

variation, including rare variation [49], at TFBSs is a major target of genetic selection [50]

and a key contributor to adaptive phenotypes [6,7,51]. Using TFBSs in accessible gene

promoter regions, we identified a total of 3,398,768 transcription factor (TF) – target

gene (TG) relationships in Nile tilapia. As we use experimental data, this is less than

the 5,900,174 TF-TG edges we *in silico* predicted in Nile tilapia in our previous work

[7], but similar to the 3,505,491 TF-TG relationships found in human based on *in silico*

predictions overlapping ENCODE footprints [52].

Using a stringent criterion to identify candidate TF-TG relationships, involving

prioritising statistically significant TFBSs with genetic variation between ecologically

divergent species and genes that exhibit high accessibility and high expression

compared to all genes, we identified 1,168 genes that could be associated to

aquaculture relevant traits, like salinity acclimation. Some tilapia species can thrive in

adverse environmental conditions, including varying levels of salinity and alkaline

water. Nile tilapia is intolerant to high salinity (optimal is up to 16 parts per thousand,

ppt) [53] and requires freshwater (pH 6-9) [54,55] whereas euryhaline species like

Alcolapia grahami, nested within the *Oreochromis* genus [56], have adapted to

extreme environments of pH 9-11.5 and high salt concentrations of >20 ppt [37,38]. In

prlr1, a gene associated with tilapia salinity response [31], a rare genetic variant

between Nile tilapia and *A. grahami* in the STAT1 TFBSs could account for osmotic

stress response in most tilapia species, but the loss of this site could enable gill

adaptation in extremophiles like *A. grahami.* This is further supported by the role of

STAT1 as an osmotic stress induced transcriptional activator [36] and differential

expression of prolactin receptors in gills of *A. grahami* and freshwater tilapia species

[35]. On the other hand, the introduction and acclimation of freshwater species, like *O.*

esculentus, to saline/alkaline waters e.g., Lake Rukwa in Tanzania [44,45], could be

driven by genetic variation at the SREBF2 TFBS, and account for differential

expression of *cldnh,* a gene responsible for reorganising gill tight junctions in

response to salinity exposure of freshwater tilapia [41]. Salinity acclimation first

requires the detection of osmotic changes and then secondly, a physiological

response to restore osmotic homeostasis. Accordingly, excessive ions are secreted

by specialised cells in the gill, ionocytes, containing ion pumps and transporters [57,58].

As a result, there are differential gill-specific transcriptional responses to salinity

exposure in different tilapia species, triggering turnover of ionocytes as well as

immune and cell stress response [59]. We therefore suggest that the interactions of

both STAT1-*prlr1* and SREBF2-*cldnh* are likely involved in salinity acclimation along

the tilapia phylogeny. Discrete rewiring of existing ancestral variation at these

important functional loci could be a mechanism to allow populations to rapidly adapt

to new ecological niches e.g., *O. esculentus* introductions to Lake Rukwa [60], and

also form the basis for breeding genotypes of desirable traits into farmed strains.

This novel epigenome of not only Nile tilapia gill, but the first recognised assessment

of open chromatin in any fish gill tissue, will enable a better functional annotation of

noncoding regions to identify causative variants associated with aquaculture relevant

traits. Now that the ATAC-seq protocol has been optimised for tilapia fish, we can

characterise the open chromatin landscape in the other 26 tilapia species to confirm

and prioritise variants identified in this study, and define trait loci for other

environmental traits e.g., temperature tolerance. The novel methods and resources

generated here can be ultimately used to guide genomic selection programmes

aimed at the genetic improvement of species to acclimate to adverse environmental

conditions.

Figures

Fig. 1 – Annotation of open chromatin peaks in Nile tilapia gill. Fold enrichment

of open chromatin (accessible) peaks overlapping coding and noncoding regions in

the Nile tilapia genome. Circles show enriched annotated region (y-axis) of

significance (FDR <0.05, to right) and fold enrichment (x-axis) values of all annotated

peaks. Number of peaks overlapping each annotation shown by size of each circle.

Fig. 2 – Correlation of accessible peaks accounting for gene expression

change in Nile tilapia gill. (A) Average *log2* gene expression (as transcripts per

million - TPM, y-axis) and average *log2* ATAC signal (as gene promoter peak counts,

x-axis) for each gene across the three replicates, split into four categories based on

peak summit distance to transcription start site (TSS). Correlation co-efficient (*R,*

blue trendline) and *p-value* shown for each category. **(B)** Average *log2* gene

expression (as transcripts per million - TPM, y-axis) and average *log2* ATAC signal

(as all gene promoter peak counts i.e., TSS-peak up to 5000 bp category in Fig. 2a,

x-axis) for each gene across the three replicates, split by high accessibility and high

expression to left (HA-HE - both average TPM and ATAC signal values are above

the 70th percentiles) and to right, medium-low accessibility and high expression (MA-

ME - average ATAC signal count less than the 50th percentile and TPM higher than

the 70th percentile). Correlation co-efficient (*R,* blue trendline) and *p-value* shown for

each category.

Fig. 3 – Single nucleotide polymorphisms (SNPs) in the Nile tilapia genome. (A)

Coalescent phylogeny of 27 tilapia species and 2 outgroups inferred using ASTRAL

(Ciezarek, A. *et al.*, bioRxiv TBC, 2023) with number and identity of SNPs in each

species based on mapping to the Nile tilapia genome. Phylogenies inferred based on

14,535 10 kb windows across the genome. Units = coalescent units; All posterior

probabilities = 1.0. Species photo credits: George Turner, Martin Genner, Antonia

Ford, Benjamin Ngatunga, Geraldine Kavembe, and Fishbase (Luc de Vos, Brain

Gatwicke, Andrew Nightingale, and Royal Museum for Central Africa). **(B)** Fold

enrichment of SNPs overlapping coding and noncoding regions in the Nile tilapia

genome. Circles show enriched annotated region (y-axis) of significance (FDR

<0.05, heatmap to right) and fold enrichment (x-axis) values of all SNPs mapped to

the Nile tilapia genome. Number of SNPs overlapping each annotation shown by

size of each circle. **(C)** Fold enrichment of SNPs overlapping open chromatin

(accessible) peaks in noncoding regions of the Nile tilapia genome. Circles show

enriched annotated region (y-axis) of significance (FDR <0.05, heatmap to right) and

fold enrichment (x-axis) values of all SNPs in annotated noncoding peaks. Number

of noncoding SNPs in annotated noncoding peaks shown by size of each circle. **(D)**

Gene ontology (GO) biological process enrichment of accessible gene promoter

regions containing SNPs in the Nile tilapia genome. GO terms are subset for

enrichment of -log10 (FDR < 0.05) of more than 10, with the full figure provided as

Supplementary Fig. S5. Circles show enriched term (y-axis) of significance (FDR

<0.05, heatmap to right) and fold enrichment (x-axis) values of GO terms. Number of

genes with promoter regions containing SNPs shown by size of each circle.

Fig. 4 – Prioritising genetic variation of TFBSs in accessible peaks accounting

for gene expression change in Nile tilapia gill. (A) Tag-count (TC) score of TF

footprints (y-axis) and TFBS bit-score of motif match (x-axis) of genome-wide

predicted TFBSs based on footprints in accessible gill peaks. **(B)** Circos plot of open-

chromatin peaks (orange), footprints (blue), TFBSs (maroon), SNPs (green), and

gene promoter regions (black) on each Nile tilapia chromosome (outer track).

Fig. 5 – Accessible peaks in the Nile tilapia *prlr1* gene promoter with variation at the STAT1 TF footprint. (A) Nile tilapia

track of the *prlr1* gene sequence (blue annotations) in LG7 with accessible peaks across three biological gill replicates (orange

peaks), TF footprints (maroon marks) and tilapia SNPs (green marks). **(B)** Expanded *prlr1* gene promoter region (blue annotation)

of accessible peaks (in orange) across three gill replicates above the STAT1 TF footprint (maroon mark) and containing a SNP

(green mark with purple circle). **(C)** Line plot profile of the STAT1 TF footprint (n=1261) across Nile tilapia gene promoter regions

showing positional (x-axis) signal of activity (red line, y-axis) centred on the footprint (at position 0) with flanking sequence.

Expanded STAT1 TF footprint shown to left and original input motif used for predicting the site shown to right. **(D)** Variation from the

SNP in Fig. 5b demarcated in the STAT1 TF footprint with homozygous reference (red dots), homozygous alternate (green dots)

and heterozygous (yellow dots) alleles for the SNP shown for each species in the tilapia phylogeny (based on Fig. 3a).

Fig. 6 – Accessible peaks in the Nile tilapia *cldnh* gene promoter with variation at the SREBF2 TF footprint. (A) Nile tilapia

track of the *cldnh* gene sequence (blue annotations) in LG10 with accessible peaks across three biological gill replicates (orange

peaks), TF footprints (maroon marks) and tilapia SNPs (green marks). **(B)** Expanded *cldnh* gene promoter region (blue annotation)

of accessible peaks (in orange) across three gill replicates above the SREBF2 TF footprint (maroon mark) and containing a SNP

(green mark with purple circle). **(C)** Line plot profile of the SREBF2 TF footprint (n=2125) across Nile tilapia gene promoter regions

showing positional (x-axis) signal of activity (red line, y-axis) centred on the footprint (at position 0) with flanking sequence.

Expanded SREBF2 TF footprint shown to left and original input motif used for predicting the site shown to right. **(D)** Variation from

the SNP in Fig. 6b demarcated in the SREBF2 TF footprint with homozygous reference (red dots), homozygous alternate (green

dots) and heterozygous (yellow dots) alleles for the SNP shown for each species in the tilapia phylogeny (based on Fig. 3a).

Materials and Methods

Tissue dissection

All animal procedures were approved by University of Stirling and carried out in accordance with approved guidelines. Three male *O. niloticus* individuals were sacrificed according to Home Office schedule 1 killing using overdose of MS-222 (tricaine) at University of Stirling, UK. The gill raker, arch and filaments were dissected from each individual, and one half was stored in RNAlater (1:5 ratio) for naked DNA and RNA extraction, and the other half immediately used for ATAC cell preparation.

Cell preparation

Around 50,000 cells were harvested from the gill filaments by taking a 1mm biopsy punch, counting nuclei and then spun at 500×g for 5 min at 4°C. Cells were washed once with 50µl of ice-cold 1× PBS buffer and pelleted at 500×g for 5 min at 4°C. Cell pellets were gently resuspended in 50µl of 0.05% cold lysis buffer (10mM Tris-HCl pH7.4, 10mM NaCl, 3mM $MgCl_2$, 0.05% IGEPAL CA-630), and immediately pelleted at 500×g for 10 min at 4°C and then stored on ice.

Transposition reaction and purification

Pelleted nuclei were gently resuspended in a 50 µL transposition reaction mix composed of 25 µL 2× TD Buffer (Illumina), 2.5 µL Tn5 Transposes (Illumina) and 22.5 µL Nuclease-Free H_2O. Transposition reaction was incubated at 37°C for 30 min and purified using the PCR purification MinElute Kit (QIAGEN), according to

manufacturer's protocol. Transposed DNA was eluted in 10 µL Elution Buffer (10mM

Tris buffer, pH 8) and stored at -20°C.

PCR amplification

Transposed DNA was amplified in a final volume of 50 µL composed of 10 µL

Transposed DNA, 10 µL Nuclease Free H_2O, 2.5 µL 25µM P7 adapter, 2.5 µL 25µM

P5 adapter and 25 µL NEBNext High-Fidelity 2x PCR Master Mix (NEB).

Transposed DNA was amplified for 5 min at 72°C, 30 secs at 98°C, and 11 cycles of

10 secs at 98°C, 30 secs at 63°C and 1 min at 72°C in a PCR thermocycler.

Amplified transposed DNA was purified using the PCR purification MinElute Kit

(QIAGEN) and eluted in 20 µL Elution Buffer (10mM Tris buffer, pH 8), according to

manufacturer's protocol. To remove excess primers for final ATAC libaries, an

additional 1× Agencourt AMPure XP bead (Beckman Coulter) clean-up was

performed and eluted in 0.1× filtered TE. ATAC libraries were quantified on the Qubit

4 fluorometer (Invitrogen) and size distribution assessed on Agilent Tapestation

and/or Bioanalyser.

DNA extraction

DNA was purified from gill filaments using the DNeasy Blood and Tissue kit

(QIAGEN) according to manufacturer's protocol. DNA was quantified on the

Nanodrop 2000 (Thermo Scientific) and Qubit 4 fluorometer (Invitrogen), and used 1

ng for DNA library preparation using the Nextera XT DNA Library Preparation kit

(Illumina), according to manufacturer's protocol. Library size distribution was

assessed on Agilent Tapestation and/or Bioanalyser. DNA libraries, obtained from

naked DNA, were used as internal controls to determine background levels of

genomic DNA accessibility and Tn5 transposase sequence cleavage bias.

ATAC and control DNA sequencing

Three ATAC and three corresponding naked DNA control libraries were equimolar

pooled and 50 bp paired-end sequenced at Earlham Institute on the Illumina

NovaSeq 6000 platform using an S2 flow cell, generating an average of 90 million

(ATAC-seq) and 16 million (naked DNA control) reads per library.

ATAC-seq and control DNA processing

Sequence adaptors were removed and trimmed for quality from raw paired-end

reads using Trim Galore! (v 0.6.5) (https://github.com/FelixKrueger/TrimGalore) and

FastQC (v 0.11.9) [61] using default parameters. Read alignment, post alignment

filtering and ATAC peak calling were performed according to the ENCODE projects

'ATAC-seq Data Standards and Processing Pipeline' for replicated data

(https://www.encodeproject.org/atac-seq/). Briefly, trimmed reads were mapped to

the Nile tilapia reference genome (*O. niloticus* UMD_NMBU) [26] using bowtie2

(v2.2.6) [62], with parameters '−k 4 −X2000 −mm' and outputted in BAM format using

SAMtools (v1.9) [63]. Since ATAC-seq generates high proportions (15-50% in a typical

experiment) of mitochondrial mapped reads, any reads mapping to the mitochondrial

genome were identified using BLAST (v2.3.0) [64] and removed from the BAM file

using SAMtools (v1.9) [63]. The resulting BAM files were sorted, and duplicated reads

were marked using Sambamba v0.6.5 [65]. Duplicated, unmapped, non-primary

alignment, and failing platform QC reads were filtered out using SAMtools (v1.9) [63],

retaining reads mapped as proper pairs, and fragment length distributions were

plotted using Picard (v1.140) (https://github.com/broadinstitute/picard/). At each step,

the recommended parameters from the ENCODE pipeline were applied. BAM files

were converted to *tagalign* files using Bedtools (v2.30.0) [66] and Tn5 shifting of ATAC

mappings carried out prior to peak calling. Peaks were identified using macs2

(v2.1.1) [67,68] with the shifted tag as test and corresponding control DNA as input with

parameters '−f BED −p 0.05 −−nomodel −−shift −75 −−extsize 150'. Narrow

peaks were used to create coverage tracks using *bedClip* and *bedToBigBed* in the

UCSC-tools package (v333) (http://hgdownload.cse.ucsc.edu/admin/exe/). Following

the ENCODE pipeline, Irreproducible Discovery Rate (IDR) peaks of true replicates

were flagged as either true (<0.1) or false (≥0.1) using idr v2.0.4

(https://github.com/kundajelab/idr), taking reproducible (true) peaks between

replicates. The fraction of reads in peaks (FRiP) were calculated using Bedtools

(v2.30.0) [66] and demarcated as pass (>0.3) or acceptable (>0.2) according to

ENCODE guidelines. FRiP was not used as a QC measure and instead, transcription

start site (TSS) enrichment was calculated using ATACseqQC (v1.18.0) [69], with the

TSS enrichment QC requirement of a significant signal value at the centre of the

distribution being applied. All samples passed this criterion for further analysis. A

union of peaks from all three biological replicates was created and used for

subsequent analyses.

Identifying conserved noncoding elements (CNEs)

We use a similar approach as applied previously [5] to call CNEs in Nile tilapia based

on evolutionary constraint in a five cichlid species phylogeny. A multiple genome

alignment (MGA) of four cichlid genomes (*M. zebra* UMD2a [70]; *P. nyererei* v1 [5]; *A.*

burtoni v1 [5]; *N. brichardi* v1 [5]) and Nile tilapia (*O. niloticus* UMD_NMBU [26]) was

created using Cactus (v2.0.3) [71] and outputted in Multiple Alignment Format (MAF).

A neutral substitution model was created using the *phyloFit* function of PHAST (v1.5)

[72] by fitting a time reversible substitution 'REV' model and parameters '--tree

`"((((Metriaclima_zebra,Pundamilia_nyererei),Astatotilapia_burtoni),N`

`eolamprologus_brichardi),Oreochromis_niloticus)" --subst-mod REV`'.

The five cichlid MGA was split by *O. niloticus* chromosomes/scaffolds using the

mafSplit function in the UCSC-tools package (v333)

(http://hgdownload.cse.ucsc.edu/admin/exe/).

The neutral substitution model and MGAs of each *O. niloticus* reference

chromosome/scaffold were used as input to predict conserved noncoding elements

(CNEs) using the *phastCons* function of PHAST (v1.5) [72] with parameters '--

`target-coverage 0.3 --expected-length 30 --most-conserved --`

`estimate-trees --msa-format MAF`'. Conservation score outputs were used to

define highly conserved CNEs (hCNEs) with sequence identity ≥90% over ≥30bp

and pseudo accelerate/diverged CNEs (pseudo aCNEs) with sequence identity

<90% over ≥30bp. The evolutionary conservation-acceleration (CONACC) score of

each pseudo aCNE was predicted by running *phyloP* [73] of the PHAST (v1.5)

package [72] using the likelihood ratio test (LRT) '`--method LRT`' on the CNE --

`features` with their corresponding neutral substitution model in '`--mode CONACC`'.

Pseudo aCNEs with a negative CONACC score, likelihood ratio <0.05, and

significant divergence (altsubscale >1), were defined as significantly deviating from

the neutral model, and therefore as true aCNEs.

Peak annotation and enrichment

Up to 5 kb gene promoter regions were annotated in the *O. niloticus* UMD1 [26]

genome according to the method used in our previous study [7]. Narrow peaks either

overlapping or most proximal to all annotated features [26] in the genome were

mapped using the *intersect* function of Bedtools (v2.30.0) [66], and each peak

assigned to a feature and/or gene accordingly. The enrichment of accessible peaks

in coding and noncoding regions was tested using the Genome Association Tester

(GAT) tool [74]. The accessible peaks were provided as segments of interest to test, a

bed file of annotations to test against, and workspace as the length of each

scaffold/chromosome. GAT was ran using the following parameters: `--verbose=5,`

`--counter=segment-overlap, --ignore-segment-tracks, --qvalue-`

`method=BH --pvalue-method=norm`. We use the Benjamini-Hochberg [75] false

discovery rate (FDR) to assess enrichment of peaks in annotated regions, with a

statistical cut-off of FDR < 0.05.

Gene Ontology (GO) enrichment

GO enrichment analyses of genes was conducted using the 'g:GOst' module of

g:Profiler (https://biit.cs.ut.ee/gprofiler/gost) [76], version e105_eg52_p16_e84549f

(February 2022), using the *O. niloticus* database. We use the false discovery rate

(FDR) corrected hypergeometric *p*-value to assess enrichment of GO terms, with a

statistical cut-off of FDR < 0.05.

Transcription factor (TF) footprinting

TF footprints were characterised using HINT-ATAC in the Regulatory Genomic

Toolbox (v0.13.0) [77] using a stringent false positive rate (FPR) of 0.0001, with both

Nile tilapia specific and cichlid-wide position weight matrices (PWMs) as defined in

our previous study [7], as well as vertebrate PWMs from JASPAR (v9.0) [78],

HOCOMOCO [79], GTRD [80], and UniPROBE [81]. TF footprint line plots were generated

with the 'differential analysis' module of HINT-ATAC in the Regulatory Genomic

Toolbox (v0.13.0) package [77] using bias-corrected signals. Redundant TFBSs in the

same, or overlapping positions were filtered based on selecting the highest bit-score

of motif match for each overlapping TF.

RNA extraction and sequencing

RNA was purified from each tissue using the RNeasy Plus Mini kit (QIAGEN)

according to manufacturer's protocol. RNA and DNA content were quantified on the

Qubit 4 fluorometer (Invitrogen) and integrity assessed on Agilent Tapestation and/or

Bioanalyser, taking samples with RIN≥7 and <15% genomic DNA. A total of 45/55

(82%) samples passed these criteria for selection (Supplementary Table S2). A total

of 45 stranded RNA libraries were prepared using the NEBNext Ultra II Direction

RNA-seq kit according to manufacturer's protocol. All stranded RNA-seq libraries

were equimolar pooled and 150 bp paired-end sequenced at Earlham Institute on 1

lane of the Illumina NovaSeq 6000 platform using an S4 v1.5 flow cell, generating an

average of 70 million reads per library.

RNA-seq processing

Read quality was assessed using FastQC (v 0.11.9) [61] and Trim Galore! (v 0.6.5)

(https://github.com/FelixKrueger/TrimGalore) was used to remove adapters and trim

for low-quality from the raw paired-end reads using default settings. All reads were

then mapped to the *O. niloticus* UMD1 genome [26] using HISAT2 (v 2.2.1) [82] with

default parameters. Mapping QC was carried out using QualiMap (v 2.2.1) [83] with

default 'rnaseq' parameters. The final BAM file was sorted using samtools (v1.16.1)

[63] and transcript abundance was calculated using 'htseq-count' in the HTSeq (v

2.0.2) [84] package.

Identifying ATAC peak and gene expression association

Given the large number of accessible peaks and overlapping genes (127,602 peaks

and 20,248 genes), we devised an approach to reduce and identify the peaks that

could regulate their gene targets expression. For gene expression, we use an

approach applied previously [85] to calculate transcript per million (TPM) values by first

normalizing the transcript count by the gene length, as calculated using GTFtools [86],

followed by the library size, as calculated using QualiMap (v 2.2.1) [83], and then

carrying out a *log2*(x +1) transformation of 1) each genes TPM in each replicate; and

2) the mean TPM for each gene across biological replicates. Each genes mean TPM

across the three replicates is used to assess correlations with ATAC signal whereas

replicate specific TPM are used to study any differences between replicates. The

ATAC signal was processed using an approach applied previously [87] to obtain the

number of independent Tn5 insertions in collated gene promoter peaks; the number

of insertion sites (peak counts) was counted using collated narrow peaks against a

merged BAM file of all three replicates using Bedtools (v2.30.0) *coverage* [66]. After

creating a peak count matrix, the counts matrix was normalised using edgeR [88]

counts per million (CPM) 'log=TRUE, prior.count=5' followed by a quantile

normalization using the preprocessCore

(https://github.com/bmbolstad/preprocessCore) *normalize.quantiles* module in R (v

4.4.2). After merging the three replicates ATAC signal using the *log2* average from

the normalized counts matrices, the average *log2*-TPM and *log2*-ATACSignal for

each gene was plotted with the correlation co-efficient (r) calculated in R (v 4.4.2).

Based on an approach devised previously [30] to categorise putative activated,

repressed or poised genes, peak-gene relationships are assigned to one of four

groups according to lower than 50th (medium-low) and higher than 70th (high)

percentiles of gene promoter accessibility (*log2*-ATACSignal) and gene expression

(*log2*-TPM). The four groups are (1) MA–ME (medium–low accessibility and

medium–low expression); (2) HA–HE (high accessibility and high expression); (3)

HA–ME (high accessibility and medium–low expression); (4) MA–HE (medium–low

accessibility and high expression). Any genes that did not fall into one of the four

groups were not used in the analysis to maintain stringent gene groups.

Identifying SNPs with exclusive variant types between Nile tilapia and other

species

The VCF file of the 69 million SNPs mapped to the Nile tilapia (*O. niloticus*

UMD_NMBU [26]) reference genome in our previous study (Ciezarek, A. *et al.*, bioRxiv

TBC, 2023) was first normalised to split multiallelic sites into multiple rows using

bcftools (v 1.12) [63] with the parameters 'norm −m−any −0v'. After outputting the first

four columns from the resulting file, we use bcftools 'query' to tabulate the number

of samples having each variant type, and then bcftools 'view' to report each sample

with each type of variant. SNPs that are present in prioritised TFBSs of candidate

genes are then filtered for variant types (heterozygous and/or homozygous alternate)

that are exclusive to Nile tilapia and any other species.

Declarations

Data Availability

All sequencing data generated for this article is available under the ENA study accession PRJEB59919. All other data underlying this article is available in the article, its supplementary material or in the following repository: https://doi.org/10.6084/m9.figshare.22100825.

Competing interests

The authors declare that they have no competing interests.

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Author contributions

KR and DP sacrificed and dissected fresh fish tissues; TKM prepared tissue-specific

cells to perform transposition reactions and purifications for ATAC libraries; TKM and

AM performed tagmentation of genomic DNA controls, library amplification and QC;

AC identified variants in the tilapia phylogeny; TKM processed ATAC-seq and RNA-

seq data, identified CNEs, annotated peaks with enrichment analysis, ran GO

enrichment, identified TF footprints, and identified ATAC peak and gene expression

associations; TKM and WH wrote the manuscript with input from AM, AC, KR, DP

and FDP.

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